ASSESSING PUBLIC PERCEPTIONS OF SAFETY AND IDENTIFYING EARLY ADOPTERS: A CASE OF AUTONOMOUS VEHICLES IN MICHIGAN

By

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ABSTRACT

Autonomous vehicles (AVs) have the potential to revolutionize transportation by improving safety, reducing accidents, enhancing traffic flow, and increasing fuel efficiency. Despite their numerous benefits, public acceptance of AVs remains a challenge due to concerns related to safety, liabilities, and control. This study aims to understand public perceptions of AVs, perceptions of AVs safety and their impact on adoption and policy development. Using a unique dataset comprising surveys of 1000 Michigan residents, census data, and other relevant information, this research addresses these key research questions: (1) Does the perception of the safety of autonomous vehicles (AVs) vary depending on different timeframes and conditions? (2) How do the public perceive and react to the different fears associated with riding in autonomous vehicles (AVs)? (3)What factors impact people's willingness to use autonomous vehicles in the future? (4) Is there a correlation between individuals who are early adopters of other technologies and their inclination to embrace autonomous vehicle technology early on?

The study reveals that most individuals in Michigan feel safe riding in AVs during light traffic, daytime, and within their own town, while feeling less comfortable during heavy traffic, nighttime, and on highways. Gender is a significant differentiating factor, with males generally feeling safer in all situations. Demographic factors such as age, household income, and employment status also influence comfort levels, with younger employed individuals exhibiting higher acceptance compared to older retired individuals. Familiarity with AV technology reduces concerns related to software or hardware malfunctions and vehicle breakdown. Additionally,

individuals who are less aware or less positive about AVs require more time before embracing the technology. Furthermore, early adopters of other technologies, including text messaging, smartphones, social media, transportation apps, car sharing, and smart home technology, are more likely to be early adopters of AVs.

The findings of this study provide valuable insights for AV technology developers regarding public perceptions in Michigan. Recommendations are made to target specific communities and regions for information initiatives and development interventions to maximize the benefits of AV implementation. By understanding public perceptions of AV safety and identifying early adopters, this research contributes to the knowledge base necessary for the successful integration of AVs. Decision-makers can leverage this information to address concerns, build public trust, and facilitate widespread adoption of AV technology. Moreover, identifying early adopters offers valuable input for marketing campaigns, policy formulation, and infrastructure planning.

I dedicate this thesis to my husband Muhammad Sufyan for his love and support throughout this journey and my children Musa and Abdul Hadi who let me study and achieve my goals. My love for my parents inspired me; success is the result of love.

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CHAPTER 1 - Introduction

Laying the background

The emergence of autonomous vehicles (AVs) has brought about significant advancements in transportation technology. AVs have the potential to revolutionize the way we travel, offering benefits such as increased safety, enhanced efficiency, and improved accessibility. However, the successful integration of AVs into our society depends not only on their technical capabilities but also on public acceptance and perception of their safety. Understanding public perceptions and identifying early adopters are crucial steps in ensuring a smooth and successful transition to an AV-dominated future.

The twentieth century observed a revolution in commuters with the mass production of affordable cars allowing people to drive themselves freely from A to B. In the twenty-first century, technology and automotive companies are working to realize a new passenger transport revolution: fully autonomous vehicles, which – by removing the need for a driver – are expected to reduce the number of collisions resulting from human driving error and improve road safety. Although some forms of autonomous vehicles, such as driverless trains (Lo, 2012) and airport shuttles (TRL, 2016), have been in common usage in cities for a number of years, these modes of transport run along enclosed routes and are therefore limited in terms of their movements and interactions with vehicles or people other than passengers.

On the contrary, autonomous cars will, in theory, be moving amongst other road users along public routes, thus their interactions with people will be, and may be perceived to be, more complex. Some surveys have been conducted in recent years on the public's perception of autonomous cars, but have typically focused on people as users of such vehicles (Bansal et al., 2016; JD Power, 2013; Kyriakidis et al., 2015; Schoettle and Sivak, 2014; Smith, 2016).

Perceptions from a user point of view, for example, what timeframes and locations, autonomous cars will be safe to use and what are the factors corresponding to early adoption of this complicated innovation, have received little attention to date. Likewise, there has been little attempt to determine if early adopters of other technology will be early or late adopters of AVs. This study will report the findings of a survey with participants residing in Michigan investigating perceptions of autonomous vehicles, particularly with regards to road safety and acceptance. Perceptions are compared in relation to early adoption, risk/concerns, and participant socio-demographics.

This research focuses on assessing public perceptions of safety and identifying early adopters of autonomous vehicles in the state of Michigan. Michigan is a hub for automotive innovation and has played a significant role in shaping the future of transportation. With its rich automotive history, diverse population, and numerous AV testing sites, Michigan provides an ideal setting to examine public perceptions and identify key factors influencing the adoption of AVs. Specifically, the research aims to explore the general attitudes and concerns of the public regarding the safety of autonomous vehicles, investigate the factors that influence public perceptions of AV safety, such as demographics, prior technology adoption, and familiarity with AV technology.

After more than 15 years of technological advancements, the anticipated arrival of autonomous vehicles brings with it a sense of uncertainty. This lack of certainty should not come as a surprise, as Lipson and Kurman (2016) explain in their book "Driverless: Intelligent Cars and the Road Ahead." In their work, they identify seven myths commonly associated with automated vehicles. These myths include the belief that driver assistance technology will seamlessly lead to fully autonomous vehicles, the idea that progress in this field is a linear process, the perception that the general public is resistant to adopting autonomous vehicles, the notion that substantial investments in infrastructure are necessary for their implementation, concerns about the ethical dilemmas these vehicles may face, the expectation that autonomous vehicles must be flawless, and the belief that their adoption will happen suddenly and dramatically.Seven years after the publication of Lipson and Kurman's book, these seven myths continue to be significant and address contentious issues that greatly concern those closely connected with the developments in disruptive mobility.

The current emphasis on AVs is not a recent phenomenon. For almost a century, the industry has been making promises to mitigate accidents, alleviate traffic congestion, and address the inconveniences associated with our car-dependent society by leveraging advanced technologies (Norton, 2021). Whether viewed positively or negatively, whether delivered punctually or with delays, self-driving technology possesses the potential to bring about transformative changes and even disrupt traditional practices in transportation and land usage (Faisal, Kamruzzaman, Yigitcanlar, & Currie, 2019; Guerra, 2016; Fuller, 2016).

Viewing AVs as a disruptive innovation (beyond their potential to disrupt the environments they operate in) brings a fresh perspective to the assessment of this technology. It challenges the notion that AVs are merely substitutes for conventional vehicles and opens up the possibility of them being the catalyst for broader changes, such as replacing mass transit or introducing an entirely new category of mobility. The introduction of these autonomous vehicles in our communities necessitates a deeper understanding of how public perceptions of AVs will, in turn, impact our communities.

Levels of automation

Vehicle automation levels refer to the classification system that categorizes the extent of automation and driver involvement in operating a vehicle. The levels, commonly known as the SAE (Society of Automotive Engineers) automation levels, provide a standardized framework for understanding the capabilities and responsibilities of automated vehicles. The SAE automation levels range from Level 0 to Level 5, representing different degrees of automation.

1. Level 0 - No Automation: At this level, the driver is fully responsible for all aspects of driving. The vehicle does not possess any automated features and relies entirely on the driver's control and input.
2. Level 1 - Driver Assistance: This level involves the introduction of basic automated features that assist the driver in specific tasks. Examples include systems like adaptive cruise control or lane-keeping assist. However, the driver remains fully responsible for operating the vehicle and must actively monitor the driving environment.
3. Level 2 - Partial Automation: Level 2 introduces a higher degree of automation, where multiple automated features can operate simultaneously. These features can control acceleration, braking, and steering, but the driver must remain engaged, supervise the system, and be ready to take control when necessary. Examples include advanced driver-assistance systems (ADAS) like Tesla's Autopilot or GM's Super Cruise.
4. Level 3 - Conditional Automation: At Level 3, vehicles can perform most driving tasks under specific conditions and environments. The automated system can handle driving tasks, but the driver must be ready to intervene when prompted by the system. Transitioning control between the automated system and the driver may require a short notice period.

5. Level 4 - High Automation: Level 4 vehicles are highly automated and can operate without driver intervention under specific conditions and within specific geographic areas. They can handle most driving tasks and respond to unforeseen events. However, there may be situations where the driver is required to take over control. Level 4 automation is designed for specific use cases or environments, such as self-driving shuttles or autonomous taxis.
6. Level 5 - Full Automation: Level 5 represents full automation, where the vehicle is capable of performing all driving tasks under any conditions and without human intervention. Level 5 vehicles do not require a human driver and can operate in a wide range of environments, including complex urban scenarios or challenging weather conditions. However, true Level 5 automation is still in development and is not yet commercially available.

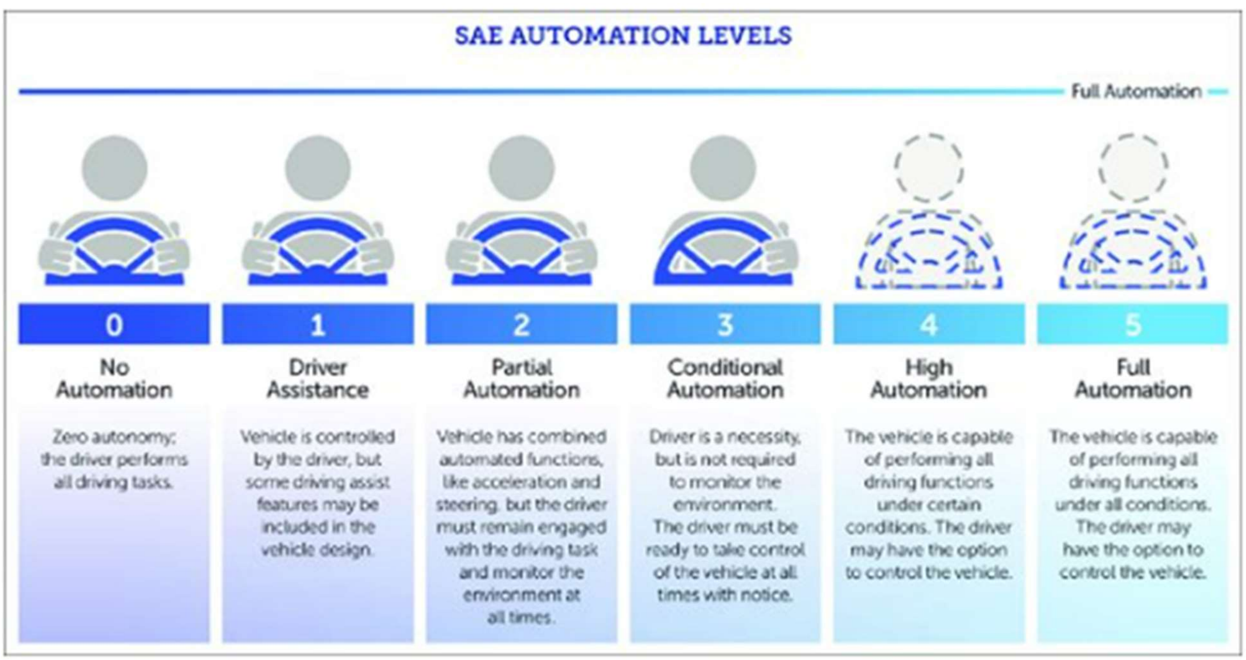

Figure 1: Levels of automation set forth in SAE J3016 standard (SAE International 2016). Reprinted from NHTSA (2017).

Distinguishing between different levels of automation is significant for two key reasons. Firstly, levels one to three represent a progression of vehicle technology currently available in the market, offering incremental improvements in safety and convenience without fundamentally altering the way mobility products are utilized. On the other hand, levels four (L4) and five (L5) signify automated technologies that enable users to initiate and complete trips without human intervention. L4 vehicles operate within defined conditions, while L5 vehicles are designed to operate under all conditions. The introduction of autonomous vehicles represents a transformative shift in the mobility landscape, with the potential to redefine who travels, how people travel, and consequently, how society functions. This study specifically focuses on L4 and L5 vehicles, as they embody the prevailing perceptions regarding the capabilities of automated vehicles.

In 2018, the perception of autonomous vehicles (AVs) among Americans underwent a significant shift. Initially characterized by cautious optimism, this perception transformed into one of distrust and uncertainty following two notable incidents. Firstly, a fully automated Uber (now Aurora) test vehicle in Tempe, Arizona struck and killed a pedestrian during its testing phase (Griggs & Wakabayashi, 2018). Shortly thereafter, a Tesla Model X, with its automated support feature called Autopilot engaged, crashed into the median barrier on Highway 101 in Mountain View, California, resulting in the driver's death (Noyes, 2020). Although these incidents were isolated, the public, influenced by media coverage, interpreted them as failures of automated driving to fulfill its primary promise of enhanced safety (Penmetsa, Sheinidashtegol, Musaev, Adanu, & Hudnall, 2021). Consequently, 2018 marked a turning point where creators and developers of Level 4 and Level 5 autonomous driving solutions realized the need for significant additional efforts to establish trustworthy systems in the eyes of the public.

Problem Statement

The domain of automated driving is often seen as potentially disruptive and experiencing delays. While the technology is familiar to the robotics and mobility industries, it lacks widespread understanding among the general population. Building public trust and generating interest are crucial aspects of introducing any new technology, as they promote consideration and a positive reputation. Despite over fifteen years of technical advancements and media coverage, the future of automated vehicles remains uncertain.

Autonomous vehicles (AVs) are expected to generate a variety of benefits, including minimizing accidents, improving traffic flow, improving mobility and increasing fuel efficiency (NHTSA, 2017). Among the concerns reported by people when asked about AVs, safety was by far the most frequent (Casley, Jardim, & Quartulli, 2013). How safe AVs are perceived to be has a significant impact on their implementation, development, and ultimately their use. Research shows tremendous potential of AV safety and suggests that an understanding of public perceptions of safety is useful in assessing the potential future adoption of the technology. In particular, they are expected to make traveling safer, cheaper, more comfortable, and more sustainable, and thus will open car travel to children, seniors and people with disabilities (Fagnant and Kockelman 2015). For significant segments of the population, driving is simply not a feasible option. They may be limited by the cost of full-time car ownership, the cost of learning to drive, difficulties with licensing, or factors related to health, disability, or age. For these communities, the difficulty in accessing transportation also leads to socioeconomic disadvantage. Ahead of the potential positive benefits of allowing underserved communities to experience better transportation options and personalized transportation choices, autonomous vehicle technology could also empower those unable to drive and provide equity and justice to all socio-demographic groups of people. For the elderly, those too young to drive, the blind, the disabled, and others, the autonomous vehicle will provide unparalleled, independent access to transportation. Realizing these benefits to society, as well as to individual users, will require rapid and widespread adoption of AV technology. Thus, there is a clear need for state and local government policies that support the deployment of technologies.

Many researchers have explored the role of public perceptions and acceptance in greater adoption of AVs (Fagnant and Kockelman, 2018; Litman, 2018; Hohenberger et al., 2017; Bansal and Kockelman, 2017; Gold et al., 2015; Heide and Henning, 2006). AVs should conform to traffic regulations to reduce the likelihood of injury and death while furthering transport flow (Vamplew et al., 2018). Envisaging safety upsides on the ground is associated with technological developments in addition to the extent and rate of autonomous vehicle acceptance, which are shaped by public perceptions (Moody et al., 2020). Greater road safety is one of the key benefits of autonomous vehicles because these systems assume control of critical safety tasks, the type often prone to human error (NHTSA, 2017). Several studies suggest that the potential for improved safety is a key determinant of the general public's willingness to use AVs (Casley, Jardim, & Quartulli, 2014). Therefore, perceptions of AV safety may help determine the extent to which people will accept and use AVs and the rate at which their safety benefits may be realized on the road. However, current literature largely fails to account for how perceptions of AV safety differ across individuals and how those differences may impact the rate and scale of AV adoption.

Many of the issues inhibiting the shift to AVs are technological and financial. Considerable progress has been made in improving the AV technologies and reducing costs. Equally important however, is the need to overcome market resistance to AVs. Unless and until most of the population is comfortable with using this mode of transportation much of the potential benefit will be unrealized. The Institute of Electric and Electronics Engineers (IEEE) reported that the "biggest barrier to pervasive adoption of driverless cars may have nothing to do with technology but will be general public acceptance. While the average driver may grasp the basic benefits of autonomous cars—increased fuel efficiency and safety, along with a reduction in traffic—it may not be enough to get them to let go of the steering wheel" (Newcomb, 2012).

Early adopters of technology

Early adopters of technology play a crucial role in shaping public perceptions and acceptance of new innovations. In the context of autonomous vehicles (AVs), understanding the characteristics and attitudes of early adopters is of significant importance. Early adopters are individuals who are more willing to embrace and adopt technological advancements before the general population. Early adopters, who are typically more open to adopting new technologies, can serve as catalysts for widespread acceptance and adoption of AVs. Their positive experiences, endorsements, and willingness to try and embrace new technologies can influence public perceptions and attitudes. By understanding the characteristics and motivations of early adopters in the context of AVs, we can gain insights into how their positive experiences can shape the opinions and behaviors of the wider public.

Moreover, studying early adopters can help identify the key factors that drive their adoption decisions and preferences. These factors may include personal values, technological familiarity, socioeconomic status, risk perception, and prior experiences with similar technologies. By examining these factors, we can gain a deeper understanding of the drivers and barriers to AV adoption, as well as potential strategies to address concerns and increase public trust.

Additionally, early adopters can provide valuable feedback and insights during the development and implementation stages of AV technology. Their experiences and suggestions can help identify areas for improvement, refine safety measures, and enhance user experiences. Their input can inform policymakers, manufacturers, and technology developers, guiding the development of AV systems that align with public needs and expectations.

This study aims to explore the significance of early adopters of technology in shaping public perceptions of autonomous vehicles. By investigating the potential correlation between the early adoption of other technologies and the accelerated acceptance of AV technology, I seek to uncover insights that can inform strategies for promoting acceptance, addressing concerns, and fostering a positive perception of AVs among the wider population. Through this research, I hope to contribute to the successful integration of AVs into our transportation systems, ultimately leading to safer, more efficient, and sustainable mobility solutions for the future.

Research Questions

1. Is public perception of AVs safety affected by different timeframes and conditions?
2. What are the public's perceptions regarding the various types of fears associated with riding in autonomous vehicles (AVs)?
3. What are the factors influencing the willingness to use autonomous vehicles in the future?
4. Do individuals who embrace other technologies early on show a greater tendency to be early adopters of autonomous vehicle technology?

Aim of the Study

The purpose of this study is to investigate the public perceptions surrounding the safety of autonomous vehicles and identify if there is a stronger inclination for individuals who readily embrace emerging technologies to also be early adopters of autonomous vehicle. The study seeks to understand how the general public perceives the safety aspects of autonomous vehicles. It aims to explore attitudes, beliefs, concerns, and expectations related to the safety of autonomous vehicles among residents in Michigan and aims to identify the factors that influence public perceptions of safety. This includes examining demographic variables, such as age, gender, education, and income, as well as other potential factors like familiarity with autonomous vehicle technology. This information can provide insights into the potential target audience for autonomous vehicle adoption campaigns and help in developing effective strategies for promoting acceptance and adoption. This study aims to contribute to the existing body of knowledge on autonomous vehicles and public perceptions. By focusing on the specific context of Michigan, it provides valuable insights into the opinions and behaviors of residents in a region known for its automotive industry. The findings can also serve as a basis for future research and comparative studies in other geographical areas.

Readers Guide

In the following chapters the reader will find:

Chapter 2, a review of literature associated with the purviews of this study;

- Perceptions of safety,
- Early adopters of technology,
- Theoretical framework
- Acceptance of new technologies.

Chapter 3, methodological foundation, data acquisition and analysis plans

- Research procedures, hypotheses,
- Data acquisition tool (SOSS),
- Analytical methods used.

Chapter 4, research results,

- An overview and an analysis of the quantitative data collected from 1000 respondents,
- Descriptive and inferential analysis as ways to understand the respondents, their insight and what that insight may mean more broadly,
- Tables to facilitate an understanding of the quantitative data of the survey.

Chapter 5, discussion,

- Provides a summary of the results presented in chapters 4 and more broadly, an interpretation of the results to the domains of advanced/disruptive technology acceptance, communications, and influence, and also provides recommendations in the areas of future research.
- Policy implications of this research

CHAPTER 2 - Literature Review

Public perceptions of autonomous vehicles

There is a cluster of research investigating what factors correspond to increased interest in AVs, more positive attitudes regarding the technology, and higher willingness to adopt, use, and buy them. Many studies have identified young adults and men as two demographics that hold more positive attitudes towards autonomous vehicle technology (Nielsen & Haustein, 2018; Anania, et al., 2018; Hulse, Xie & Galea, 2018; Lee, et al., 2017). In particular, young people and men have been shown to agree more strongly that AVs will improve safety (Nielsen & Haustein, 2018), have fewer concerns about vehicle safety (Kyriakidis, Happee & de Winter, 2015; Schoettle & Sivak, 2014), and have increased willingness to use the technology (Smith & Caiazza, 2017; Payre, Cestac, & Delhomme, 2014). Hulse, Xie, and Galea (2018) argue that the positivity towards AVs among young males could lead to more rapid road safety benefits should they quickly adopt AVs once the technology is introduced. However, two studies found no correlation between interest in or intention to use automated vehicles and age (Zumud et al., 2016, Shin & Shunsuke, 2017). This suggests there is some uncertainty around whether younger people will be the first to adopt an automated vehicle. In addition to young adults and men, college educated people and people living in urban areas have also been found to have more positive attitudes towards AVs, including increased willingness to use the technology (Smith & Caiazza, 2017; Schoettle & Sivak, 2014) and increased perceptions of safety (Schoettle & Sivak, 2014; Nielsen & Haustein, 2018).

The researchers are faced with an important consideration regarding the level of awareness and knowledge among consumers regarding automated vehicles. Many stated preference studies often overlook the awareness or knowledge of respondents, which poses challenges in assessing the reliability of the findings from these studies. Survey participants may encounter difficulties in evaluating a technology they are unfamiliar with. Abraham et al. (2016) conducted a study where respondents were asked about their familiarity with 15 automated driving systems. The findings indicated that familiarity was highest for "Active Cruise Control" and "Autopilot," but more than half of the sample had no knowledge of these two systems. The researchers concluded that the majority of consumers are "not familiar at all" with automated vehicles. A similar level of awareness was observed in a study conducted by Kelly Blue Book (2016), where 21% of respondents had not heard of self-driving vehicles, 30% were unaware of driverless vehicles, and 69% had no prior knowledge of autonomous vehicles. Only 18% of the participants in their sample indicated a high level of knowledge about "autonomous vehicles."

Several studies have identified underlying attitudinal factors that also explain these perceptions (e.g., Tussyadiah, Zach, & Wang, 2017; Nees, 2016; Choi & Ji, 2015). AV technology is at an early stage of development. Studies to understand user perception of these cars and expectations from this technology are important in refinement of this technology (Feroz. et al,2018).

Perceptions of Safety

Although road infrastructure and technology are significant influences on the safety of AV systems, public perception of safety is important in understanding how travel behavior may respond to the introduction of AVs on roads. Awareness of direct relations between safety perceptions and willingness to change travel behavior can shed light upon the potential safety benefits that may be realized through AVs (NHTSA, 2017). Several studies have identified that the same socio-demographic factors correlated with increased perceptions of AV safety are also associated with increased intention to adopt AV technology (Smith & Caiazza, 2017; Payre, Cestac & Delhomme, 2014; Hulse, Xie & Galea, 2018). Furthermore, research has suggested that perceptions of safety are related to interest in and intended use of AVs, meaning an understanding of perceptions of safety is useful in anticipating the potential future adoption of the technology. In one survey conducted in the U.S. in 2013, 59.5% of respondents indicated that the safety of AVs had a positive influence on their desire to purchase the technology and 82% of respondents indicated that safety was the most influential appeal of AVs, ahead of cost (Casley, Jardim & Quartulli, 2014). However, other studies have found much smaller proportions of people who rate safety as a primary motivation for interest in AV technology, such as 17% among American adults (Smith & Caiazza, 2017) or 31% across an international sample (Lang, et al., 2016).

Just as there is evidence that positive perceptions of AV safety might motivate its use, concerns about safety may also be a major driver of lack of interest in AVs across countries. Among respondents in an international sample who indicated they were unlikely to take a ride in a fully self-driving vehicle, 50% did not feel safe if the car was driving itself, 45% expressed desire to be in control of the vehicle at all times, and 23% would be concerned the car could be hacked (Lang, et al., 2016). Kyriakidis, Happee, and de Winter (2015) found that 64.5% of respondents agreed that automated driving worries them because of safety and reliability concerns. Thus, the literature suggests that safety perceptions are a major aspect of AV adoption but may also be a motivator for adoption among certain groups.

Numerous studies have substantiated the effect of the environment in the AV specific context. For individuals who rode in an AV under controlled conditions, experiential feelings of safety during the ride were found to considerably predict increased behavioral intention to use, buy, and recommend AVs, as well as eagerness to take additional rides in AVs (Xu et al., 7 2018). Several other studies have found that attitudes towards AV safety prior to actual use extensively influence intention to adopt and use AVs. One study found that attitudinal factors regarding contextual acceptability of AVs, including attitudes towards safety, correlated positively with intention to use AVs, intention to buy the technology, and willingness to pay for the technology (Payre, Cestac & Delhomme, 2014). A recent study found that perceived safety risk was a significant contributor to feelings of trust towards AV technology and that this trust was the strongest contributor towards intention to use and purchase AVs in the future (Zhang et al., 2019). These studies suggest that individual perceptions of safety may play a large role in shaping the adoption and use of AVs in the future and are therefore important in understanding the technology's resulting impact on safety.

Public perception of AVs' safety and trust

User acceptance is the main key for the success of any new technology. Casley, Jardim and Quartulli (2014) conducted a survey in the US with 467 respondents with the goal of understanding the impact of three factors on the public acceptance of AVs. These three factors are the safety of the system, the cost of the technology, and the liability issue. Respondents were asked to rank the importance of safety, costs, and laws on their perception of AVs. Eighty two percent of the respondents ranked safety as the central aspect in order to adopt AVs. The results demonstrate that safety is the main concern for people and that people will not adopt AVs until they feel it is safe.

Rezaei, and Caulfield (2020) conducted an international survey which showed that people were not likely to believe in the safety and security of AVs' operation. The study results demonstrate that 44% of the respondents do not believe that AVs are safer than a normal human driver, while 25% believe AVs are safer. Furthermore, 66% of respondents indicated that they will not feel safe if the vehicle does not have a steering wheel, contributing to a larger proportion of people who feel unsafe, while only 14% have no problem if the vehicle does not have a steering wheel.

Several other studies globally and across years illustrate that people have pressing concerns regarding AVs' safety. A survey done in the US, UK and Australia shows that 92% of the respondents are highly concerned about the safety of the AV in poor weather and about the interaction between the vehicle and pedestrians (Schoettle and Sivak, 2014). Another survey in the US shows that 69% of the participants are highly concerned about the safety of the AV system (Schoettle and Sivak, 2015). The survey by Kyriakidis et al. (2015) that received responses from 109 countries demonstrates that 76% of the respondents are highly concerned about the safety of the AV system. Additionally, the survey by Greaves et al. (2018) in Australia shows that 68% of the respondents are highly concerned about the safety of the AV system. Therefore, concerns regarding the safety of AVs is crucial. Autonomous vehicles are less desirable if perceived unsafe, in spite of their assistance. Conducting a study on the public perceptions of AV safety in Michigan holds great importance, as it enables us to gain insights into how residents perceive the safety aspects of this emerging technology. This includes understanding their views on its overall safety, the conditions under which they perceive it as safe or unsafe, and the underlying factors that shape their perspectives. Given this specific concern, it is crucial for manufacturers of autonomous vehicles to prioritize and highlight the safety of AVs. They need to demonstrate to the public that riding in an AV is not a risky or dangerous experience.

Early Adopters of Technology

Thousands of new technological ideas are envisioned every year. An ability to innovate these ideas has been and will continue to be critical in surviving the current world. Hence, the diffusion of technological innovations and consumer adoption behavior has continued to be an important issue for researchers over the past few decades. While some scholars have devoted significant research activities on developing theoretical models (Venkatesh, 2003; Davis et al., 1989) to explain the phenomenon, others have sought empirical support for the conceptualizations (Cheng et al., 2006). However, as decisions are taken under the influence of technology acceptance, most of these researchers focus on categorizing the perceptions of the technology attributes, called innovation characteristics.

There is evidence in the literature to suggest that there are benefits to be gained from being able to identify and target early adopters of an innovation (Goldsmith & Flynn, 1992; Mcdonald & Alpert, 2007). The early adopters are important for the success of a technology, as they provide companies and policy makers with insights on how the new technology will function on a daily basis. They will also show others that the technology is safe.

Understanding the key attributes of early adopters is obviously of theoretical and practical relevance to behavioral science (Bartels & Reinders, 2010). From a theoretical perspective, it will enable researchers to develop richer theoretical models to explain the adoption behavior across different types of user groups (Agarwal & Prasad, 1998). It will also assist practitioners in targeting the relevant consumers to facilitate the distribution of an innovation.

Theoretical framework

Conceptually, there are two primary theoretical explanations used to understand adoption and use of technological innovations among early adopters and late adopters. The first relates to the personal characteristics such as income level, age, gender and level of education of consumers that determine their innovative behavior. The second explanations assume that there is a generalized unobservable predisposition referred to as "innate innovativeness" (Hirchman, 1980) that influences user innovative behavior.

Demographic Variables

Demographic profiling is the process of splitting the market by considering personal similarities and differences, such as gender, age, marital status, occupation, income, and household structure. Such descriptive attributes have been used in most consumer analysis studies. The relationship between socioeconomic characteristics and consumer behavioral intentions has been widely researched by both innovation diffusion and technology adoption researchers (Im et al., 2003; Meuter et al., 2005). For example, Wei (2001) studied the socioeconomic characteristics of mobile phone laggards in Hong Kong, Tjøstheim and Boge (2001) studied the demographic characteristics of early adopters of mobile commerce when compared to non-adopters, while Mante-Meijer and Haddon (2001) did the same for general mobile services like voice and messaging. However, in spite of this attention, their effect on technology adoption is found to be less significant or often conflicting. The level of education of an individual is found to be directly related to their level of resources, and hence their ability to experiment and adopt new technological innovations (Chia, Li, Detenber, & Lee, 2006; Van den Bulte, 2000). However, the effect of income and age on innovativeness has enjoyed mixed results from innovation diffusion studies. While Im et al. (2003) and Steenkamp, Hofstede, and Wedel (1999) found no significant effect of income, age and education, Tellis et al. (2009) reported a positive correlation. Tellis et al. (2009) in a cross-country study of consumer innovativeness posits that the five demographic variables of age, income, mobility, education and gender are key predictors of consumer innovativeness. Furthermore, a study by Goldsmith et al. (1995) showed that innovative consumers are in general better educated and younger than the general population, have higher incomes and occupational status, and are more often female than male.

Consumer Innovativeness

Innovativeness influences the speed at which the adoption of a product takes place after it has entered the market. Innovation diffusion research on consumer innovativeness has studied innovativeness on three different dimensions: Innovative Behavior (IB) which deals with a realized (actualized) innovativeness, Personality Traits Innovativeness (PTI) also referred to as innate innovativeness and Domain-Specific Innovativeness (DSI). A number of researchers have taken a measure of time to assign individuals to adopter categories. Wei (2001) applied this concept in classifying all those who have not adopted cellular phones in Hong Kong by 1998 to be "Laggards". Hirschman (1980), in trying to relate innovativeness to inherent novelty seeking argued that innovative behavior can be subdivided into: vicarious, adaptive and innovative. Vicarious innovativeness measures the individual's new information seeking abilities over a given timeframe, whereas adoptive innovativeness measures the individual's actual purchase of products within a given timeframe. Use innovativeness is defined as the use of an existing product in an unusual way. However, this dimension of consumer innovativeness has been heavily criticized. First, it has been criticized as giving very little meaning to what leads to innovative behavior and therefore does not explain why an individual will be among the first to adopt an innovation. It therefore does not offer an ability to predict the behavior of innovators and early adopters (McDonald & Alpert, 2007). This is probably the most crucial limitation of Roger's measurement of innovativeness (Agarwal & Prasad, 1998). Also, by definition, both Midgley and Dowling (1978) and Flynn and Goldsmith (1993) argued that innovativeness is a hypothetical construct and thus should not be measured as an observable phenomenon.

Acceptance and Use of New Technologies

The last decade has witnessed an explosion in the availability of new vehicle technology. Like the information technology that was introduced into homes and businesses in the 1980s, new vehicle technologies will not benefit users unless they are accepted and used. In the special case of self-driving vehicles, the potential societal benefits (e.g., enhanced safety, reduced congestion, improved air quality) of these vehicles will not be achieved unless they are accepted and used by a critical mass of drivers. Research on this topic can gain much value from the rich history of forerunner research pertaining to acceptance and adoption of information technology.

In the domain of vehicle technology, acceptance has been defined as the "degree to which an individual incorporates the system in his/her driving, or, if the system is not available, intends to use it" (Regan et al., 2014). With fully autonomous vehicles, the intent to use is an important concept because the technology is not yet on the market. Intent to use is based on level of acceptance. It is not until a product becomes tangible and drivers have an opportunity to experience it "for real" that they can form judgments and provide reliable and valid responses to questions pertaining to actual use.

The significance of demographic variables on acceptance and use

The significance of demographic variables is uncertain, as different studies have found conflicting results. Schoettle and Sivak (2014) found age to be a significant variable in a survey of individuals 18 years and older in the U.S., the U.K., and Australia. Younger respondents, regardless of country, were more interested than older respondents in having self-driving technology. Likewise, Deloitte Consulting found that younger persons were more favorable about fully self-driving vehicles than older respondents in their 2014 Global Automotive Consumer Study (Sommer, 2013). On the other hand, Kyriakidis, et. al.(2015) surveyed people in 109 countries and found that neither age nor gender were significant factors; however, they did find that willingness to pay for self-driving technology was associated with income and vehicle kilometers of travel . Similarly, researchers at the University of California at Berkeley also found income to be associated with adoption of self-driving technology (Howard and Dai 2015).

The CTAM (Car Technology Acceptance Model) suggests that trust and perceived safety in the technology surfaced as influencing factors. Safety concerns were related to performance of self-driving vehicles in mixed traffic and driving performance relative to humans (Schoettle and Sivak, 2014). Matters of trust were associated with data privacy and software hacking (Kyriakidis et al., 2015), and issues of control (Howard and Dai, 2015).

CHAPTER 3 - Research Method

Research Procedure

While significant research has explored what factors contribute to an individual's perception of AVs, much of the findings are limited to random standardized sampling. Existing comparisons have been limited to descriptive statistics and bivariate correlations that often fail to account for multivariate relations among individual socio-demographics, public perceptions, and travel behavior (Lang, et al., 2016; Kyriakidis, Happee & de Winter, 2015; Sommer, 2013). This study builds on existing literature by providing a statewide comparison of perceptions of AV safety. These data allow for a precise multivariate regression model technique that assigns sample variance to individuals in a state. I can thereby explore how much of observed differences in levels of AV awareness as well as current perceptions and future predictions of AV safety are attributable to individuals in different travel time frames.

This study examines the subjective sense of safety experienced by individuals while riding in AVs, specifically focusing on the preferred time of day and situations in which people tend to feel the most secure. Furthermore, this study aims to identify the demographic profiles of individuals across the state who exhibit the highest levels of awareness regarding AVs and hold the most positive perceptions of AV safety at present. Additionally, the study seeks to explore their predictions regarding the future timeframe when they believe AVs will reach a level of safety that they are comfortable using. This individual level analysis leverages my sample's state coverage and my model's multivariate approach to support and extend existing literature on public perception of AV safety. Based on previous research, the following hypotheses are proposed:

H1: Individuals who are fully employed, high income, and highly educated, who may have the means to be early adopters of AV technology when it becomes available, also have positive perceptions of AV safety that are linked to increased intention to use AVs in the future.

H2: People feel safer riding in an AV in light traffic and in their town than in situations like at night, heavy traffic, during the day, on the highway. Males will feel safer under all conditions.

H3: People who are fully aware about AVs are more likely to fear hacking while riding in an AV.

H4: People who are less aware/ less positive about AVs will require more time before they are willing to use them.

H5: People who are early adopters of other technologies (smartphone, text messaging, Facebook, transportation apps and car-sharing such as Uber/Lyft) are more likely to be early adopters of autonomous vehicles.

Survey design

Michigan State of the State Survey (SOSS)

Manufacturers and regulators of AVs should consider whether a market for this modern innovation exists and the degree to which stakeholders will have to innovate and modify to meet customer needs and concerns. To address this issue, Michigan State University's Institute for Public Policy and Social Research (IPPSR) was contacted. A number of questions for the project were included in the 2022 Michigan State of the State Survey (SOSS) that gauged Michigander perceptions of AVs. SOSS is a quarterly statewide telephone survey of a random sample of approximately 1,000 adult residents throughout Michigan.

As part of the survey, participants were asked a set of background information questions including their gender, ethnic background, age, level of education, income, political party preference or membership, and what they view as the most pressing transportation problems within the community. Further, they were asked whether they are early adopters of other technologies like transportation apps, social media apps, car sharing apps etc. In addition, participants were also asked various questions about AVs. The term "autonomous vehicle" was used, throughout the majority of the survey. The term autonomous vehicle is defined as a vehicle that has features which operate without direct driver input, noting that no human driver is needed in a completely autonomous vehicle. The study started by asking participants a set of preliminary questions, including whether riders heard of autonomous vehicles, whether they would be willing to ride in one in at different time frames of the day, what are the possible fears they picture in their mind, and when these vehicles will become safe enough to be considered normal as conventional vehicles.

Michigan State University's State of the State online Survey (SOSS) was launched online in March 2022. YouGov interviewed 1055 Michigan residents who were then matched down to a sample of 1000 to produce the final dataset. The respondents were matched to a sampling frame on gender, age, race, and education. The frame was constructed by stratified sampling from the full 2019 American Community Survey (ACS) 1-year sample with selection within strata by weighted sampling with replacements (using the person weights on the public use file).

The matched cases were weighted to the sampling frame using propensity scores. The matched cases and the frame were combined, and a logistic regression was estimated for inclusion in the frame. The propensity score function included age, gender, race/ethnicity, years of education, and region. The propensity scores were grouped into deciles of the estimated propensity score in the frame and post-stratified according to these deciles. The weights were then post-stratified on 2016 and 2020 Presidential vote choice, and a four-way stratification of gender, age (4-

categories), race (4-categories), and education (4-categories), to produce the final weight for the sample.

Survey Questionnaire

For this study, 1,000 Michiganders were interviewed as a part of the State of the State Survey. The survey asked respondents to answer basic demographic questions including income, employment, gender, educational attainment, community type (urban or rural), and age etc. Individuals were asked to report their familiarity with autonomous vehicles, answering the question "How familiar are you with autonomous vehicle technology?" with one of four ordered choices—"Not familiar at all", "Not very familiar", "Somewhat familiar", and "Very familiar." Individuals were asked if they are an early adopter of technology, answering the question, "Are you an early adopter of the following technology: Social Media, Transportation apps, car sharing (Uber/Lyft), Smart home technology, smartphone, Text messaging, as compared to other Americans?" with one of six choices – "Have not used", "Much later", "Somewhat later", "Average", "Somewhat earlier", or "Much earlier". Further, individuals were then asked about willingness to ride in an AV: "Would you want to ride in an AV if you had the opportunity?" with these four choices – "I don't know", "No", "Unsure/maybe", or "Yes." The next question asked about respondents' comfort level in different timeframes, "How comfortable would you feel riding in an AV in 0- 1 year from now", "2-4 years from now", "5-10 years from now", or "More than 10 years from now" with one of the four ordered choices, "Very uncomfortable", "Somewhat uncomfortable", "Somewhat comfortable", or "Very comfortable." The next question ascertained the safety aspect of sitting in an AV by asking "How safe would you feel riding in an autonomous vehicle - In heavy traffic, In light traffic, At night, During the day, In your town, and On the highway?" Responses were recorded on a 1-4 scale from 1 being "Not at all safe" to 4 being "Very safe." Finally, the last question ascertained the types of fear respondents were the most concerned about while sitting in an AV with options including – "hacking", "accident due to software or hardware malfunction", "breakdown of the vehicle", and "others" with one of the four choices, "Not concerned at all", "A little concerned", "Somewhat concerned", or "Very concerned."

Respondent Profiles

Table 1 provides individual demographic data on the respondents to the SOSS for Michigan. The respondents were 54% female (n = 539) and 46% male (n = 461). The highest number of respondents were between 31 and 42 years of age as well as between 63 and 64 years of age (n = 1000) . Most of the respondents were white (85%) (n = 851), married (48.3%) (n = 483), high school graduate or GED holder (34%) (n = 339) and college graduates (four years) (17%) (n = 171), fully employed (45%) (n = 454), high income ($100,000 to $149,000) (11%) (n = 111), and living in a suburban area (38.5%) (n = 385). Comparing select variables to the census data, the sample looks similar to the state as a whole on age, race, education, mean adults and children in the household, household income, urban/rural area occupancy, and inclination to be married. Consequently, the survey respondents are relatively representative of the state.

Demographic Variables	State	SOSS
	Gender	
% Male	50	46

Table 1:Individual Demographics

Table 1 (cont'd)

% Female	50	54
Mean age		53
	Race	
% White or caucasian	79	85
% African American/Black	14	11.7
% Hawaiian or other Pacific Islander		0.2
% Asian	3.4	2.1
% American Indian or Alaska Native	0.7	1.3
% Other		2.5
	Marital Status	
% Married or remarried		48.3
% Divorced		12.7
% Separated		1.1
% Widowed		4.2
% Member of an unmarried couple		7.5
% Single, never been married		25.4

Table 1 (cont'd)

% Other		0.7
	Education	
% Graduate degree		11.6
% Some postgraduate		4
% College graduate(four years)		17.1
% 3rd year college/technical college graduate		11.9
% 2nd year college		10.6
% 1st year college		7.5
% High School graduate or GED holder		33.9
% Did not graduate high school		3.4
Mean adults in the house	2.5	2.2
mean children in the house		1.42
	Employment	
% Working		45.4
% Unemployed, laid off, or looking for work		5.9
% Retired		26.9

Table 1(cont'd)

% School full time		2.7
% Homemaker		7.8
% Disabled		9.8
	Income	
% $150,000 or more		5.8
% $100,000 or $149,999		11.1
% $90,000 or $99,999		4.3
% $80,000 or $89,999		4.5
% $70,000 or $79,999		6.8
% $60,000 or $69,999		6.8
% $50,000 or $59,999		9.5
% $40,000 or $49,999		10.7
% $30,000 or $39,999		11.3
% $20,000 or $29,999		11.3
% $10,000 or $19,999		8.3
% Less than $10,000		7.5

Table 1(cont'd)

	Area residents live in	
% Urban		14
% A suburb		38.5
% Small city or town, village		25
% Rural		21.8

Geospatial analysis

A geospatial analysis was conducted to associate survey responses with geographic coordinates which involved mapping and spatially analyzing survey data. This provided valuable visualizations, patterns, or spatial relationships that aid in understanding the geographic distribution of survey responses. This analysis is used here to identify where respondents live within the state of Michigan. In line with the overall population of Michigan, survey respondents are drawn from the population centers of the Detroit and Grand Rapids metropolitan areas. It is possible that respondents from Southeastern Michigan will be more familiar with automobiles generally because of their proximity to the Motor City. This potential effect will be addressed in the analysis to follow by including area of residence (urban, suburban, rural) as a possible explanatory variable.

Figure 2: Participant location map. Source: Author Analysis Procedures

Stage one

The analysis involves investigating the frequency distribution of responses to the relevant questions. Correlation analysis is conducted to assess the five hypotheses. Subsequently, multiple regression and path analysis techniques are employed to examine models that elucidate respondents' inclination towards riding in an autonomous vehicle (AV) and their projected timeframe for embracing the technology.

The first hypothesis is that *individuals who are fully employed, high income, and highly educated, who may have the means to be early adopters of AV technology when it becomes available, also have positive perceptions of AV safety that are linked to increased intention to use AVs in the future*. Four independent variables were examined to assess their relationship with the comfort level of riding in an autonomous vehicle (AV), the positive sentiment towards the technology, and the willingness to use it in the future. Initially, correlation analyses were conducted for the three ordinal variables, namely the level of education, household income, and the comfort level of riding in an AV across all time frames. A chi-square test was run to examine the relationship between the variables "Comfortable riding in an AV" and "employment." Crosstabs were generated for this independent variable since the employment question in the survey was nominal. The observed frequencies for each combination of categories were examined to determine if there was a statistically significant association between the variables.

The second hypothesis is that *people feel safer riding in an AV in light traffic and in their town than in situations like at night, heavy traffic, during the day, on the highway. Males will feel safer under all conditions.* To investigate potential gender differences in feeling safe under various situations, a chi-square test was performed. This test aimed to determine whether there were statistically significant associations between gender and the perception of safety across different scenarios. This statistical analysis will indicate if overall there is a significant association between gender and feeling comfortable riding in an AV in light traffic and in your town.

The third hypothesis is that *people who are fully aware about AVs are more likely to fear hacking while riding in an AV.* A correlation analysis was done between familiarity with AV technology and how concerned respondents are with the dangers of AVs such as hacking of AV software. The objective of this analysis is to examine the correlation between a higher level of familiarity with autonomous vehicles (AVs) and the degree of concern regarding software or hardware malfunctions and potential vehicle breakdowns. This analysis aims to determine whether there is a significant association between familiarity with AVs and the level of concern expressed towards these specific issues.

The fourth hypothesis is that *people who are less aware/ less positive about AVs will require more time before they are willing to use them.* To test this hypothesis, Pearson's correlation coefficient is utilized as a statistical measure to assess the strength and direction of the linear relationship between two continuous variables: familiarity with AV technology and a higher comfort level in riding an AV (in any time period). This coefficient helps quantify the degree of correlation between these variables.

The fifth and last hypothesis is that *people who are early adopters of other technologies (smartphone, text messaging, social media, transportation apps and car-sharing such as Uber/Lyft, and smart home technology) are more likely to be early adopters of autonomous vehicles.* To examine this hypothesis, Pearson's correlation coefficient is employed as a statistical tool to determine the direction between two continuous variables: early and late adopters of other technology and an increased comfort level when riding an AV (across all time periods). The correlations provide insights into whether individuals who are early adopters of diverse technologies like social media, transportation apps, car-sharing, smart home technology, smartphones, and text messaging exhibit higher levels of comfort when it comes to riding AVs across different time periods.

Stage two

After all the statistically significant variables are identified, the subsequent analysis aims to construct a linear model that elucidates the factors influencing respondents' willingness to ride in an AV and the estimated timeframe for their acceptance of the technology. This analysis moves beyond individual correlations and explores the interrelationships among variables within the system of AV technology acceptance. The initial step in developing the path model involves consolidating the numerous potential variables into indexes, which promotes simplicity and diminishes issues of multicollinearity in subsequent models. This study utilizes factor analysis as a methodology to condense and summarize a large number of variables into smaller factors. These factors formed by grouping together the initial set of variables, allowing for a more concise representation of the data.

After conducting factor analysis, chi-square tests are employed to analyze nominal data, while Pearson correlations are utilized for all other types of data. The result of the analysis reveals the levels of comfort that individuals possess towards autonomous vehicle technology based on various demographic factors. A Pearson correlation matrix is generated to illustrate the relationships between variables pertaining to the early adoption of technology and attitudes towards autonomous vehicles (AVs). The results contain correlation coefficients, which will signify the magnitude and direction of the relationships between the variables. The variables examined in the analysis include "Early adoption of technology," "Would ride in an AV," "Comfortable using index," "Familiarity," "Safety index," and "Concerns index." Finally, path analysis is employed to assess causal models by analyzing the connections between the dependent variable and independent variables. This method enables the estimation of both the magnitude and significance of these causal relationships. To initiate the process, a diagram is created to visually illustrate the interplay between variables. In path analysis, variables are logically arranged from left to right, representing a clear time-ordered relationship. Operationally, path analysis involves a sequence of multiple regression equations running from right to left. In order to maintain simplicity and prevent overcomplication of the model with numerous demographic variables, only those demographic variables that exhibited significant correlations with either technology adoption or familiarity were included in the multiple regression analyses. Specifically, the variables included for technology adoption were age, race (black or white), and income. For familiarity, the variables included were gender, age, income, and education. These selected demographic variables were utilized in the subsequent paths, moving from left to right in the path analysis. In essence, the analysis encompasses five regression models. The first model examines the dependent variable of willingness to ride, with its corresponding independent variables positioned to the left. The second model explored the dependent variable of preferred time to ride, along with the relevant independent variables. Additionally, a regression is conducted for the safety index, with tech adoption, familiarity, and the five selected demographic variables serving as independent variables. Another regression is performed for technology adoption, utilizing the five demographic variables. The next section presents the findings of a regression analysis that investigates the factors influencing individuals' willingness to ride in an AV, utilizing a reduced set of demographic variables.

CHAPTER 4 - Results

Introduction

This study investigates the following research questions:

- *Is public perception of AVs safety affected by different timeframes and conditions?*
- *What are the public's perceptions regarding the various types of fears associated with riding in autonomous vehicles (AVs)?*
- *What are the factors influencing the willingness to use autonomous vehicles in the future?*
- *Do individuals who embrace other technologies early on show a greater tendency to be early adopters of autonomous vehicle technology?*

The analysis begins by exploring the frequency distribution of responses to the questions of interest and then moves to correlation analysis to test the hypotheses noted below. Finally, multiple regression and path analysis are used to test models which explain whether respondents would ride in an AV and how long they say it will take before they are willing to use the technology. Five specific hypotheses are tested:

> H1: Individuals who are fully employed, high income, and highly educated, who may have the means to be early adopters of AV technology when it becomes available, also have positive perceptions of AV safety that are linked to increased intention to use AVs in the future.
>
> H2: People feel safer riding in an AV in light traffic and in their town than in situations like at night, heavy traffic, during the day, on the highway. Males will feel safer under all conditions.

H3: People who are fully aware about AVs are more likely to fear hacking while riding in an AV.

H4: People who are less aware/ less positive about AVs will require more time before they are willing to use them.

H5: People who are early adopters of other technologies (smartphone, text messaging, social media, transportation apps and car-sharing such as Uber/Lyft) are more likely to be early adopters of autonomous vehicles.

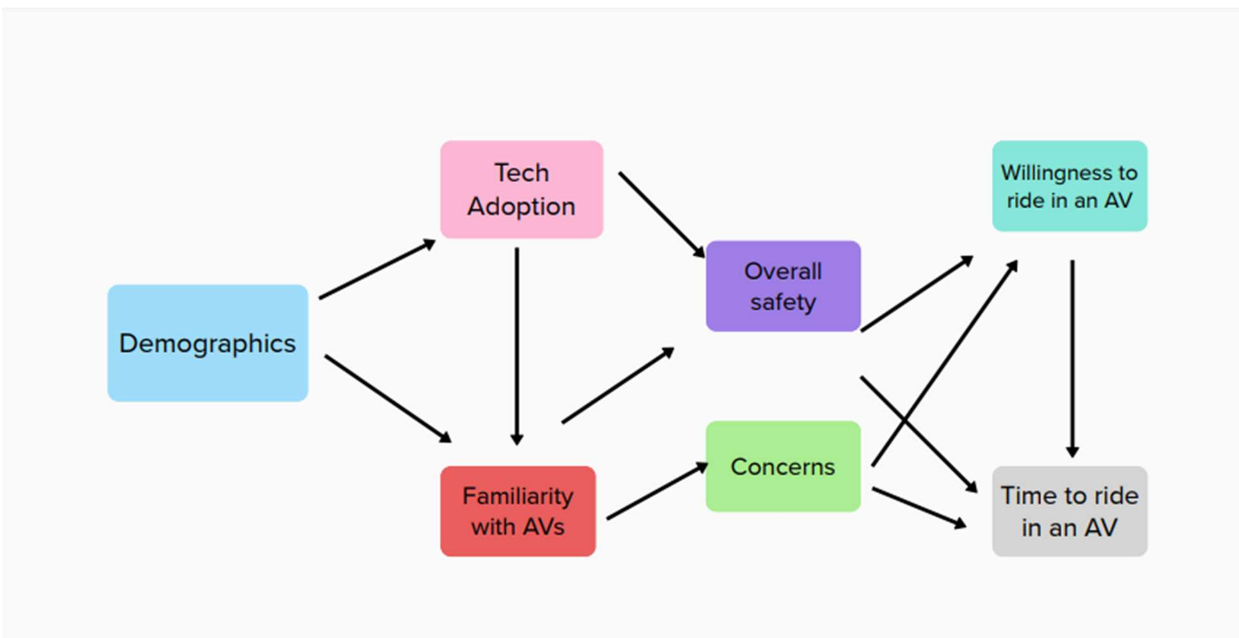

Figure 3: Hypothetical Model. Source: Author

In addition to testing the foregoing hypotheses, an explanatory model will be tested to explain whether respondents would ride in an AV and how long it will be before they would embrace the technology. Figure 3 presents the hypothetical model to be tested. It is expected that the demographic traits of the respondents will affect whether they are early adopters of technology generally as well as how familiar they are with AV technology. Early adoption and familiarity are expected to lead to perceptions that AVs are safe and fewer concerns about the technology going wrong. Finally, it is hypothesized that perceptions of overall safety and concerns about the technology will affect whether a respondent is willing to ride in an AV and how long it will be until they are ready to embrace the technology.

Attitudes about AVs

Attitudes about AV are explored using frequency data on how familiar the respondents are with the AV technology. Twenty-nine percent of the respondents are somewhat familiar with AV technology (29%) (n = 290) and 32% are unfamiliar (Table 2). Table 3 shows the percentages of respondents that would be willing to ride in an AV given the opportunity. Only 15% indicated they would be willing; 41% were unwilling and another 28% were unsure. Table 4 highlights that people mostly feel very safe or somewhat safe riding in an AV in light traffic (47%) (n =461) , during the day (48%) (n = 469) and when riding in their town (45%) (n = 448). Mostly people would not feel safe riding in an AV in heavy traffic (77%) (n = 754), at night (73%) (n = 728), and on the highway (72%) (n = 715). Table 5 shows that people would feel more comfortable riding in an AV in 5 – 10 years (43%) or after 10 years from now (47%) as compared to 0 – 4 years from now. Table 6 demonstrates the concerns people have about AVs. Generally, people are somewhat or very concerned about the dangers associated with AVs like hacking of the software (80%), accidents (87%), and breakdown of the vehicle (79%).

Familiarity with AV	
Not familiar at all	32%
Not very familiar	32%
Somewhat familiar	29%
Very Familiar	7%
Mean	2.12
N	997

Table 2:Familiarity with Autonomous Vehicle Technology

Willingness to ride in an AV if given the opportunity	
Yes	15%
Unsure/maybe	28%
No	41%
I don’t know	165
Mean	2.42
N	998

Table 3:Perceptions on willingness to ride in an AV if they had the opportunity

	% Not at all safe	%Not very safe	%Somewhat safe	%Very safe	Mean	N
In heavy traffic	48	29	19	5	1.81	986
In light traffic	34	19	34	13	2.26	985
At night	45	29	21	6	1.87	987
During the day	32	20	36	12	2.27	985
In their town	34	20	34	12	2.23	988
On the highway	45	27	20	7	1.89	986

Table 4: Perceptions of AV Safety Under Different Conditions

	% Very uncomfortable	%Somewhat uncomfortable	%Somewhat comfortable	%Very comfortable	Mean	N
0 – 1 year from now	52	24	17	5	1.74	979

Table 5: Perceptions of comfort level riding in an AV in the future

Table 5 (cont'd)

2 – 4 years from now	44	27	21	7	1.89	980
5 – 10 years from now	37	21	30	13	2.18	982
More than 10 years from now	33	19	24	23	2.38	981

	% Not concerned at all	% A little concerned	%Somewhat concerned	%Very concerned	Mean	N
Hacking of AV software	8	11	27	53	3.27	990
Accident due to software or hardware malfunction	4	8	20	67	3.51	987
Breakdown of the vehicle	6	15	28	51	3.23	988
Other	7	2	3	9	2.71	207

Table 6: Perceptions of dangers of AV

Peoples' concerns about AVs

People have expressed a wide range of concerns regarding autonomous vehicles based on the responses provided in the 'other' category of the question asking about the types of fear the respondents are most concerned about while sitting in an AV. Some individuals were worried about the reliability of the technology, fearing robot failures and malfunctions that could lead to accidents (figure 4). Other respondents are concerned about the loss of control and the vulnerability of someone else taking over the vehicle. Privacy is another significant concern, with worries about government tracking, surveillance, and potential outside control by malicious individuals. Cost-related concerns include insurance premiums, repairs, and the overall expense of owning or obtaining an autonomous vehicle. Safety is a recurring theme, encompassing worries about accidents, situational ethics, and the ability of autonomous vehicles to navigate challenging road conditions. Additionally, there are concerns about the impact on the environment, dependence on GPS, car sickness, and the potential obsolescence of human drivers. The responses also highlight concerns related to pedestrians, cyclists, crime, liability, unexpected events, data collection by big tech, and the availability of skilled technicians for AV repairs. It is clear that people's concerns about autonomous vehicles encompass a wide range of issues, reflecting the complexity and multifaceted nature of this emerging technology.

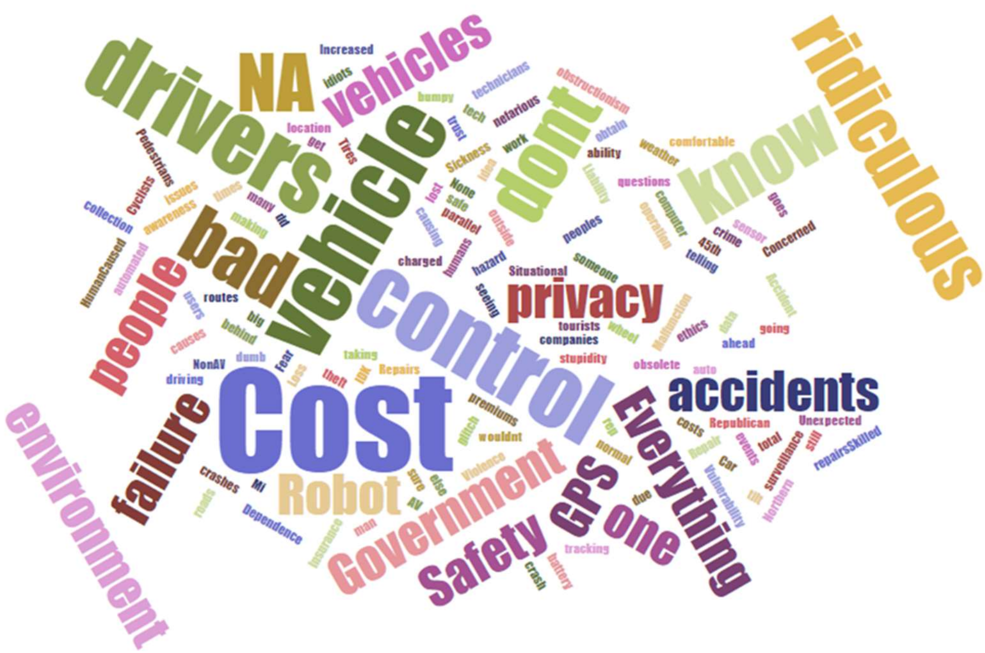

Figure 4: Word cloud created from responses of how concerned people are with the dangers of AVs other than the three options provided (i.e., hacking of AV software, accident due to software or hardware malfunction, breakdown of the vehicle). Source: Author

Comparison with 2017 SOSS

To determine if there have been any shifts in the opinions of Michigan residents regarding autonomous vehicles (AVs) over time, the responses to the 2017 State of the State Survey (SOSS), which included questions about AVs, were compared with more recent data. This comparison aimed to identify any potential changes or variations in attitudes towards AVs among the residents of Michigan. It is possible that with time, people become more familiar and hence more willing to interact with technology. Table 7 shows a comparison of the results from the SOSS launched in 2017 with the results obtained in 2022. The 2017 SOSS measured the public's views about riding on the road with autonomous vehicles. While data are not directly comparable across these two surveys due to changes in question wording, there are clear patterns that emerge in both. The main benefit of this approach is to gather information about AV users' perspective and decisions and compare these decisions on adoption of autonomous vehicles in some time frame; there is uncertainty about whether the comparison would hold moving into the future. Another benefit of this approach is to verify whether perceptions of AVs improve over time. The comparison shows that 79% of people feared self-driving cars in 2022. This is about a 50% jump from 2017 when only 26% were fearful of the technology. The survey revealed that as people become more aware of the AVs technology, they might be more fearful about the dangers. An even more telling statistic from the survey is that 22% of respondents now feel fully comfortable riding in an autonomous vehicle, which is a 21% jump from 2017. This suggests that there may be some bifurcation among respondents, with some becoming increasingly comfortable and others getting more concerned about AVs over time. The analysis of the 2022 survey to follow sheds light on this issue.

	2017 SOSS	2022 SOSS
Prior Knowledge about self-driving vehicles	92%	37%
People would ride in an AV	37%	15%
People would not ride in an AV	50%	41%
People are unsure about riding in an AV	10%	28%
Feel comfortable riding in an AV	0.9%	22%
People concerned about danger of AV	26%	79%

Table 7:Comparison of SOSS 2022 with 2017 SOSS

The 2022 survey differs from the earlier works on AVs in that it also looked at the early and late adopters of other technologies like smartphones, text messaging, social media, transportation apps and car-sharing such as Uber/Lyft. Table 8 shows that, overall, people are early adopters of technology like social media, transportation apps, smart phones, and text messaging.

However, 39% of the respondents have never used smart home technology including the voice-controlled virtual assistant Alexa, Smart TV, Smart thermostat, Smart plugs, Video doorbells, and Robot vacuums. A little more than half of the respondents have not used ride-hailing options such as Uber and Lyft. Table 9 summarizes the late and early adopters by different technology categories.

	% Have not used	% Much later	% Somewhat later	%Average	%Somewhat earlier	%Much earlier	Mean	N
Social Media	10	13	25	31.5	11	10	3.49	993
Transportation Apps	10	11	23	37	10	9	3.52	993
Uber/Lyft	55	12	12	13	4	4	2.1	992
Smart home technology	39	15	15	19	7	5	2.57	995
Smart phone	4	15	24	35	11	10	3.65	996
Text messaging	4	13	24	39	10	11	3.69	994

Table 8:Early/Late adopters of Other Technology

Early/late adopters of Technology				
	Early adopters	Average	Late adopters	Have not used
Social media	21%	31.5%	38%	10%

Table 9:Summary early/Late adopters of Other Technology

Testing of Research Hypothesis

The five hypotheses are restated below with their results.

H1: Individuals who are fully employed, high income, and highly educated, who may have the means to be early adopters of AV technology when it becomes available, also have positive perceptions of AV safety that are linked to increased intention to use AVs in the future.

The correlations between the variables in this hypothesis are reported in Table 10. There were four independent variables to test with comfort level riding in an AV, feeling positive about the technology, and willing to use it in the future. Firstly, correlations were run for the three ordinal variables i.e., level of education, household income and comfort level riding in an AV for all time frames. Neither of the variables, level of education or household income, have a statistically significant linear relationship with the comfort level of people riding in an AV in the very short term. However, respondents with higher levels of education and income are more likely to use AV technology over the longer term, specifically in 5-10 or more than ten years.

	Level of education	Household income	Comfortable riding in an AV (0 – 1 years from now)	Comfortable riding in an AV (2-4 from now)	Comfortable riding in an AV (5-10 years from now)	Comfortable riding in an AV (More than 10 years from now)
Level of education	1.00	.376**	-.032	.034	.067*	.107**
Household income	.376**	1.00	.018	.057	.077*	.101**

Table 10:Pearson correlation level of education and household income with Comfort level

- ***significant at .01 level*

Table 11 provides the results of a chi-square test examining the relationship between the variables "Comfortable riding in an AV" and "employment." Crosstabs were run for this independent variable because the employment question on the survey was nominal. The table includes the observed frequencies for each combination of categories and indicates whether the association between the variables is statistically significant. The "employment" variable indicates that there is a significant relationship between employment and the comfort level of riding in an AV at a significance level of 0.05. The finding indicated that the value of the Chi Square statistics is 41.165. The p-value is 0.001 which indicated that the result is significant. The data suggest that the variables (employment status and comfort level of riding in an AV) are associated with each other. Cross tabulation results show that respondents employed full time are more likely to feel comfortable riding in an AV.

Employment Categories	Comfortable riding in an AV (0 – 1 year from now)	Comfortable riding in an AV (2 – 4 years from now)	Comfortable riding in an AV (5 – 10 years from now)	Comfortable riding in an AV (More than 10)
Working	74%	67%	54%	49%
Unemployed, laid off, or looking for work	67%	66%	48%	47%
Retired	85%%	82%	68%	61%
School full time	77%	59%	37%	26%
Homemaker	80%	74%	59%	57%
Chi square value	41.165*	37.192	40.462	33.254

*Table 11:Chi square test results for employment, *=significant at .05 **significant at .01*

H2. People feel safer riding in an AV in light traffic and in their town than in situations like at night, heavy traffic, during the day, on the highway. Males will feel safer under all conditions. The data in Table 12 indicates that most people feel safe in conditions like light traffic(very safe - 13%, somewhat safe – 33%), during the day(very safe – 12%, somewhat safe – 35%) and in their town (very safe – 12%, somewhat safe – 33%). After running the crosstabs there is a significant difference in males' and females' feelings of safety riding in an AV in light traffic, during the day and in their town. Males feel safer in all three situations, which supports the hypothesis. A chi square test was performed with gender to see if there are significant gender differences in feeling safe under different situations. The findings indicate that overall, there is a significant association between gender and feeling comfortable riding in an AV in light traffic, during your day, and in your town with p values less than .001 for all three situations.

How safe would you feel riding in an AV **In light traffic**					Chi Square value
Gender	Not safe at all	Not very safe	Somewhat safe	Very safe	
Male	31%	16%	35%	18%	21.395**
Female	36%	22%	32%	9%	
How safe would you feel riding in an AV **during the day**					
Male	66%	19%	12%	3%	26.207**
Female	38.5%	38.5%	19%	4%	
How safe would you feel riding in an AV **in your town**					
Male	51%	29%	18%	1%	18.927**
Female	56%	24%	15%	5%	

*Table 12:Frequency table and chi square test for gender and feeling safe in an AV in different situations, **=significant at .01*

H3. People who are fully aware about AVs are more likely to fear hacking while riding in an AV. The correlation between familiarity with AV technology and how concerned respondents are with the dangers of AV such as hacking of AV software is not statistically significant (*r*=-.039, *p* > .05) (Table 13). The direction of the relationship is negative meaning if one variable increases the other decreases. Those with greater familiarity are significantly less concerned with a software or hardware malfunction and about potential breakdowns of the vehicle.

	Familiarity with AV technology	How concerned –hacking of AV software	How concerned –hacking of AV software	How concerned –hacking of AV software
Familiarity with AV technology	1.00	-.039	-.092**	-.145**
How concerned – hacking of AV software	-.039	1.00	.640**	.531**
How concerned – Accident due to software or hardware malfunction	-.092**	.640**	1.00	.657**
How concerned – Breakdown of the vehicle	-.145**	.531**	.657**	1.00

*Table 13:Pearson correlation, familiarity with AV technology and concerns, **significant at .01 level*

These results do not support the hypothesis.

H4: People who are less aware/ less positive about AVs will require more time before they are willing to use them.

	Comfort level (0 – 1 year from now)	Comfort level (2 – 4 years from now)	Comfort level (5 – 10) years from now)	Comfort level (More than 10 years from now)
Familiarity	.248**	.278**	.244**	.237**

*Table 14:Pearson correlation, familiarity with AV technology and comfort riding in different time frames *=significant at .05 **significant at .01*

Based on the results in Table 14, the variables familiarity with AV technology and higher comfort level riding in an AV (in any time period) have a statistically significant linear relationship (r= -.237, $p < .05$). The direction of the relationship is positive i.e., greater familiarity with AV technology is associated with higher comfort level riding in an AV in all the time frames. These results support the hypothesis.

H5: People who are early adopters of other technologies (smartphone, text messaging, social media, transportation apps and car-sharing such as Uber/Lyft, and smart home technology) are more likely to be early adopters of autonomous vehicles.

	Comfort level (0 – 1 year from now)	Comfort level (2 – 4 years from now)	Comfort level (5 – 10) years from now)	Comfort level (More than 10 years from now)
Early adopters of social media	.220**	.216**	.198**	.171**
Early adopters of transportation apps	.176**	.223**	.220*	.230**
Early adopters of car-sharing	.352**	.330**	.308**	.269**
Early adopters of smart home technology	.312**	.310**	.304**	.268**
Early adopters of smartphones	.226**	.217**	.198**	.175**
Early adopters of text messaging	.157**	.152**	.156**	.152**

*Table 15:Pearson correlations: Comfort level and early adopters, *=significant at .05*

Table 15 displays Pearson correlation coefficients between the comfort level for riding in autonomous vehicles (AVs) in different time frames and the early adoption of various technologies. The correlations indicate the strength and direction of the relationship between these variables.

The correlations indicate that there is a positive and statistically significant correlation between being an early adopter of social media, transportation app, car-sharing, smart home technology, smart phones, and text messaging and having a higher comfort level in riding AVs across all time frames. Overall, the correlations suggest that individuals who are early adopters of various technologies, such as social media, transportation apps, car-sharing, smart home technology, smartphones, and text messaging, tend to have higher comfort levels in riding AVs in all time periods. The data support H5, early adopters of other technology are more likely to be early adopters of AV.

Factor Analysis

The analysis just presented tested the five hypotheses posed in the study. The remaining analysis seeks to develop a linear model explaining willingness to ride in an AV and how long it will be before respondents are willing to embrace the technology. It thus goes beyond the individual correlations to examine the system of variables involved in AV technology acceptance. The first step in developing the path model is to reduce the number of potential variables into indexes which will provide greater parsimony and also reduce multicollinearity in the models to follow. In this study, factor analysis was employed to reduce and summarize the large number of variables to represent them in different smaller factors which are made up of the initial set of variables. Factor analysis is a technique that requires a large sample size. Factor analysis is based on the correlation matrix of the variables involved, and correlations usually need a large sample size before they stabilize. Tabachnick and Fidell (2001, page 588) cite Comrey and Lee's (1992) advice regarding sample size: 50 cases is very poor, 100 is poor, 200 is fair, 300 is good, 500 is very good, and 1000 or more is excellent. As a rule of thumb, a bare minimum of 10 observations per variable is necessary to avoid computational difficulties.

The factor analysis results presented in Table 16 suggest that there are four conceptually different aspects regarding attitudes about AVs. First, the variables how comfortable would you feel riding in an AV 0 - 1 years from now, 2 -4 years from now, 5 - 10 years from now, and more than 10 years from now load on a single factor representing comfort with AV technology. All of the survey questions asking about early adoption of other types of technology load on a single factor representing an "early adoption index". The questions measuring concerns about AVs including hacking of AV software, accident due to software or hardware malfunction, breakdown of the vehicle, and other load on a single "concern" factor. Finally all of the variables asking whether respondents would feel safe riding in an AV under different conditions load on a single factor 'safety index'. Higher scores on this index indicate that a respondent feels safe under more conditions. For the factor analysis the standard SPSS defaults of varimax rotation and listwise deletion of missing data were used. F-scores from the analysis were saved to create a score on the index variable.

Comfort with AV index	Factor loadings
How comfortable would you feel riding in an AV 0-1 year from now	.770
How comfortable would you feel riding in an AV 2-4 years from now	.898
How comfortable would you feel riding in an AV 5-10 years from now	.903

Table 16:Factor analysis

Table 16 (cont'd)

How comfortable would you feel riding in AV > 10 years from now	.785
Early adoption index	
Social media	.544
Transportation Apps (Waze, google maps, Maps)	.560
Car sharing(Uber/Lyft)	.495
Smart home Technology	.507
Text messaging	.637
Concern index	
Hacking of AV software	.830
Accident due to software or hardware malfunction	.861
Breakdown of the vehicle	.798
Other	.333
Safety index	
In heavy traffic	.876
In light traffic	.929
At night	.902

Table 16 (cont'd)

During the day	.933
In your town	.921
On the highway	.889

Regression Analysis

The first step in building the regression equation is to identify the significant correlations between the exogenous demographic variables driving the model and attitudes about AVs. Table 17 presents the results of a correlation analysis between respondent demographics and the AV indexes just described. Chi squares are used for nominal data, Pearson correlations are used for all other data. The people most likely to be willing to ride in an AV are younger, single, and white males. The people most unwilling to ride are Black males. The respondents who are more familiar with AV technology are educated males who have a higher household income. Results further reveal that the people who will be comfortable riding in an AV are young, single, white males with more household income. People identifying as Hawaiian Pacific Islander, Asian, Black, American Indian, Alaskan native, and Hispanic are less likely to feel comfortable riding. Results also show that people who are early adopters of other technology are more likely to be comfortable in an AV.

	Would you ride in an AV	Familiarity	Comfortable with AV index	Early Adoption index	Concerns Index	Safety index
Male Gender[a]	38.02**	115.26**	106.04**	649.155	57.4	235.43
White[a]	6.37*	.22	141.46**(more comfortable)	657.87	44.25	249.54*
Black[a]	9.00** (less likely)	1.004	165.08**(less comfortable)	699.44	46.36	295.59**
Hawaiian, Pacific Islander[a]	2.55	4.3	494.02**(less comfortable)	974**		606.12**
Asian[a]	4.48	2.1	198.92**(less comfortable)	677.1	49.42	251.29*

*Table 17:Correlations: Demographic Variables and Attitudes About AVs - a=chi square b=Pearson correlation *=significant at .05 **significant at .01*

Table 17 (cont'd)

Asian[a]	4.48	2.1	198.92**(less comfortable)	677.1	49.42	251.29*
American Indian, Alaskan Native[a]	.61	6.3	715.45**(less comfortable)	826**	102.01**	228.13
Hispanic[a]	3.06	2.66	130.44**(less comfortable)	616.25	109**	247.83*
Marital status[a]	32.02**(single, unmarried couple more likely)	20.323	598.05**(single, unmarried more comfortable)	4174.04**	317.91	1309.44
Area of residence[a]	11.83	15.38	272.85	2496	277.52*	875.06
Age[b]	-.20**		-.21**			
Education[b]	.06	.184**	.05	.075*	.164*	.084**
Employed[b]	-.06	-.044	-.08	-.002	-.059	-.102**
Children[b]	.07*	.05	.08*	.183**	.046	.09**

Table 17 (cont'd)

7-point party ID[b]	.13**	.001	.22**	0.96**	-.15*	.207**
Household income[b]	.04	.195**	.05*	.11**	.14*	.077*

	Early adoption of technology	Would ride in an AV	Comfortable using index	Familiarity	Safety index	Concerns index
Early adoption	1.00	.27**	.32**	.21**	.31**	-.17*
Would ride in AV	.27**	1.00	.68**	.17**	.67**	-.19**
Comfortable	.32**	.68**	1.00	.27**	.82**	-.27**
Familiarity	.21**	.17*	.27**	1.00		-.05
Safety index	.31**	.67**	.82**	.31**	1.00	-.34**
Concern index	-.17*	-.19**	-.27**	-.05	-.34**	1.00

Table 18:Pearson Correlation Matrix, Early Adoption of Technology and Attitudes About AVs

**significant at .05 ** significant at .01*

Table 18 represents a Pearson correlation matrix that shows the correlations between variables related to early adoption of technology and attitudes about AVs. The values in the table represent correlation coefficients, which indicate the strength and direction of the relationships between the variables. The variables included in the analysis are "Early adoption of technology," "Would ride in an AV," "Comfortable using index," "Familiarity," "Safety index," and "Concerns index." The correlation coefficient between "Early adoption of technology" and "Would ride in an AV" is .27** (significant at the .01 level), indicating a positive and moderately strong relationship between these variables. Positive correlation coefficients (values closer to 1) indicate a positive association between the variables, meaning that as one variable increases, the other tends to increase as well. Negative correlation coefficients (values closer to -1) indicate a negative association, whereas one variable increases, the other tends to decrease. The significance levels are indicated by asterisks (* and). For example, a correlation coefficient of .27 indicates that the correlation between the corresponding variables is statistically significant at the .01 level, implying that the observed relationship is unlikely due to random chance.

Overall, the table provides information about the associations between early technology adoption and attitudes about AVs. It suggests that early adoption of technology is positively correlated with being willing to ride in an AV, feeling comfortable using AVs, familiarity with AVs, safety perceptions of AVs, and concerns about AVs. The significance levels indicate the level of confidence in the observed correlations. The concern index representing concerns about potential malfunctions of the AV is not necessarily as strongly related as other indexes like willingness to ride and when respondents are willing to ride in an AV. The variables significantly correlated with willingness to ride in an AV were used in a multiple regression model with willingness to ride in an AV as the dependent variable. The results are presented in Table 19.

Variable	B	Standard error	Beta	t	Significance
Tech adoption	.085	.044	.13	1.925	.056
Safety	.457	.046	.69	9.96	<.001
Concerns	.046	.043	.066	1.07	.29
Familiarity	-.083	.045	-.122	-1.833	.068
Gender	.095	.084	.070	1.135	.26
Race – White	-.035	.108	-.02	-.327	.744
Marital status	.016	.023	.049	.707	.480
Area you live in	-.018	.039	-.028	-.463	.644
Employment status	-.002	.003	-.031	-.543	.588
Birth Year	.000	.003	.007	.097	.923
Household income	-.013	.012	-.07	-1.088	.278
Children in the house	-.021	.054	-.025	-.382	.703
Constant	1.452	5.427		.267	.789

Table 19:Regression, Willingness to ride in an AV Adj $R^2 = .42$

Table 19 presents the results of a regression analysis examining factors influencing people's comfort level in riding autonomous vehicles (AVs). The variables considered in the analysis are as follows:

Tech Adoption: The coefficient ($B = 0.085$) suggests a positive effect on willingness to ride in an AV. However, the result is not statistically significant at the conventional threshold of 0.05 ($p = 0.056$).

Safety: The coefficient ($B = 0.457$) indicates a positive and highly significant effect on willingness to ride in an AV ($p < 0.001$, $t = 9.96$). Higher perceptions of safety are associated with a greater willingness to ride in an AV.

Concerns: The coefficient ($B = 0.046$) suggests a positive effect, but it is not statistically significant ($p = 0.29$).

Familiarity: The coefficient ($B = -0.083$) indicates a negative effect on willingness to ride in an AV, but it is not statistically significant ($p = 0.068$).

Gender, Race, Marital Status, Area you live in, Employment Status, Birth Year, Household Income, and Children in the house: None of these variables show statistically significant effects on willingness to ride in an AV, as their p-values are below the conventional threshold of 0.05.

The constant term (intercept) is 1.452, indicating a baseline level of willingness to ride in an AV.

The adjusted R-squared value of 0.42 suggests that the included variables collectively explain approximately 42% of the variance in willingness to ride in an AV. Overall, the analysis indicates that safety has the strongest positive influence on willingness to ride in an AV, while other factors such as tech adoption, concerns, familiarity, and demographic variables have either weak or non-significant effects.

Variable	B	Standard error	Beta	t	Significance
Tech adoption	.099	.047	.103	2.124	.035
Safety	.817	.049	.842	16.84	<.001
Concerns	.034	.045	.034	.76	.45
Familiarity	.015	.048	.015	.321	.75
Gender	-.034	.089	-.017	-.38	.706
Race – White	-.004	.114	-.002	-.038	.97
Marital status	.001	.024	.002	.03	.976
Area you live in	-.011	.042	-.011	-.263	.793
Employment status	.005	.003	.061	1.456	.147
Birth Year	-.007	.003	-.124	-2.304	.022
Household income	-.002	.013	-.007	-.15	.881
Children in the house	.073	.057	.06	1.274	.204
Constant	13.257	5.74		2.31	.022

Table 20:Regression, When will people be comfortable riding in an AV, Adj $R^2 = .70$

Table 20 presents the results of a regression analysis examining factors influencing people's comfort level in riding autonomous vehicles (AVs) overall all times periods. The variable tech adoption has a significant positive effect ($B = 0.099$, $p = 0.035$, $beta = 0.103$), indicating that higher levels of technology adoption contribute to increased comfort with AVs. Safety plays a crucial role in people's comfort with AVs. The variable has a highly significant positive effect ($B = 0.817$, $p < 0.001$, $beta = 0.842$), suggesting that perceived safety is strongly associated with higher levels of comfort. The concerns variable shows no significant effect ($B = 0.034$, $p = 0.45$, $beta = 0.034$), implying that concerns about malfunctions do not significantly influence people's comfort level with AVs. Familiarity with AVs also has no significant effect ($B = 0.015$, $p = 0.75$, $beta = 0.015$) on comfort, indicating that being familiar with AV technology does not directly impact people's comfort levels.

None of the variables; Gender, race, marital status, area of residence, employment status, household income, and having children in the house show statistically significant effects on comfort with AVs, as their p-values are below the commonly used threshold of 0.05. The regression model's constant term (intercept) is 13.257 ($p = 0.022$), suggesting a baseline level of comfort in riding AVs. The adjusted R-squared value of 0.70 indicates that the included variables collectively explain approximately 70% of the variance in people's comfort levels with AVs. Overall, the analysis highlights that factors such as tech adoption and perceived safety significantly influence people's comfort levels with AVs, while concerns, familiarity, and other demographic variables have relatively less impact in this regard. Additionally, the only demographic variable that is significantly correlated with comfort is age meaning younger respondents are more likely to be comfortable riding in an AV in all time periods. Perceptions of safety are the best predictor of comfort levels.

Path Analysis

Path analysis is a statistical technique used to examine the relationships between variables in a proposed causal model. It allows for the assessment of direct and indirect effects of variables on an outcome variable. In path analysis, variables are represented as nodes or boxes, and the relationships between variables are represented as arrows or paths. Each path is associated with a coefficient, which represents the strength and direction of the relationship between the variables. The analysis aims to determine the direct and indirect effects of variables on the outcome variable, as well as to assess the overall fit of the proposed model to the data. It helps researchers understand the complex interplay of variables and the mechanisms through which they influence each other. Path analysis can be particularly useful in fields such as social sciences, psychology, and economics, where researchers are interested in exploring causal relationships between multiple variables. It allows for the testing of hypotheses and the identification of key factors that contribute to the outcome of interest. By analyzing the paths and coefficients in a path analysis, researchers can gain insights into the underlying mechanisms and pathways through which variables influence each other and ultimately affect the outcome of interest.

Path analysis is used to evaluate causal models by examining the relationships between the dependent variable and independent variables. This method is used to estimate both the magnitude and significance of causal connections between variables. To begin, a diagram is drawn to serve as a visual representation of the relationship between variables. In path analysis the variables should be logically arrayed from left to right in a clear time-ordered relationship. Operationally, path analysis consists of a series of multiple regression equations running from right to left. The statistic indicated on each path is the beta drawn from the successive multiple regressions. It should be remembered, however, that because the data are cross-sectional, the causal implications are based on logic with the paths indicating the strength of relationships (Everitt and Dunn, 1991).

To ensure simplicity and avoid complicating the model with excessive demographic variables, I only included demographic variables that showed significant correlations with either tech adoption or familiarity in multiple regression analyses. Specifically, for tech adoption, the variables included were age, race (either black or white), and income. For familiarity, the variables included were gender, age, income, and education. These selected demographics were used in subsequent paths moving from left to right in the path analysis.

In order to construct a streamlined and concise model, I chose not to incorporate the concerns index in the analysis because it did not maintain a significant correlation with either the willingness to ride or the preferred time to ride in multiple regression.

In summary, the analysis consisted of five regressions (Fig 1): one with the dependent variable of willingness to ride and the independent variables located to the left of it, another with the dependent variable of preferred time to ride and the corresponding independent variables, a regression for the safety index with tech adoption, familiarity, and the five selected demographic variables as independent variables, a regression for tech adoption with the five demographic variables, and the remaining paths following this structure.

Variable	B	Standard error	Beta	t	Significance
Tech adoption	.06	.02	.83	2.96	.003
Safety	.464	.019	.653	23.87	<.001
Familiarity	-.037	.021	-.05	-1.74	.083
Gender	-.013	.038	-.009	-.35	.726
Race – Black	-.002	.06	-.001	-.043	.966
Birth Year	.000	.001	.002	.09	.93
Household Income	-.004	.006	-.017	-.625	.532
Level of Education	.001	.006	.004	.151	.88
Constant	1.66	2.194		.76	.45

Table 21:Regression, Willingness to ride in an AV. Adj R^2 = .445

Table 21 presents the results of a regression analysis examining factors influencing people's willingness to ride in an autonomous vehicle (AV) including the more limited set of demographic variables. The results are similar to the regression model previously presented. A summary of the findings is presented below.

The variables considered in the analysis are as follows:

Tech Adoption: The coefficient (B = 0.06) suggests a positive effect on willingness to ride in an AV. This effect is statistically significant at the conventional threshold of 0.05

($p = 0.003$, $t = 2.96$). Higher levels of tech adoption are associated with increased willingness to ride in an AV.

Safety: The coefficient ($B = 0.464$) indicates a positive effect on willingness to ride in an AV. This effect is highly significant ($p < 0.001$, $t = 23.87$). Perceptions of safety have a strong positive association with willingness to ride in an AV.

Familiarity: The coefficient ($B = -0.037$) suggests a negative effect on willingness to ride in an AV, but it is not statistically significant at the conventional threshold ($p = 0.083$, $t = -1.74$). Familiarity with AVs does not appear to have a significant direct impact on willingness to ride.

Gender, Race - Black, Birth Year, Household Income, and Level of Education: None of these variables show statistically significant effects on willingness to ride in an AV, as their p-values are above 0.05. This means that there is no strong evidence to suggest that these variables have a significant influence on willingness to ride in an AV.

The constant term (intercept) is 1.66, indicating a baseline level of willingness to ride in an AV. The adjusted R-squared value of 0.445 suggests that the included variables collectively explain approximately 44.5% of the variance in willingness to ride in an AV. Overall, the analysis highlights that factors such as tech adoption and perceived safety significantly influence people's willingness to ride in an AV. Familiarity and demographic variables do not have a strong or significant direct impact on willingness to ride.

Variable	B	Standard error	Beta	t	Significance
Tech adoption	.094	.022	.093	4.24	<.001
Safety	.80	.021	.787	36.803	<.001
Familiarity	.03	.023	.03	1.264	.21
Gender	.008	.042	.004	.18	.86
Race – Black	-.043	.063	-.014	-.674	.501
Birth Year	-.002	.001	-.042	-2.02	.044
Household Income	.005	.006	.016	.75	.454
Level of Education	-.01	.006	-.034	-1.64	.102
Constant	5.005	2.412		2.075	.04

Table 22:Regression Analysis Results for Factors Influencing Comfort in Riding an AV

Adj $R^2 = .67$

Table 22 presents the coefficients (B), standard errors, beta values, t-values, and significance levels for each variable included in the regression model, which examines when people will be comfortable riding in an AV.

The variables considered in the analysis are as follows:

1. Tech Adoption: The coefficient (B = 0.094) suggests a positive effect on people's comfort in riding an AV. This effect is statistically significant at a high level of confidence (p <

0.001, $t = 4.24$). Higher levels of tech adoption are associated with increased comfort in riding an AV over all time periods.

2. Safety: The coefficient ($B = 0.80$) indicates a positive effect on people's comfort in riding an AV. This effect is highly significant ($p < 0.001$, $t = 36.803$). Perceptions of safety have a strong positive association with comfort in riding an AV.
3. Familiarity: The coefficient ($B = 0.03$) suggests a positive effect on comfort, but it is not statistically significant at the conventional threshold ($p = 0.21$, $t = 1.264$). Familiarity with AVs does not appear to have a significant direct impact on comfort in riding.
4. Gender, Race - Black, Birth Year, Household Income, and Level of Education: None of these variables show statistically significant effects on comfort in riding an AV, as their p-values are above 0.05. This means that there is no strong evidence to suggest that these variables have a significant influence on comfort in riding an AV.

The adjusted R-squared value of 0.67 suggests that the included variables collectively explain approximately 67% of the variance in comfort levels in riding an AV. Overall, the analysis highlights that factors such as tech adoption and perceived safety significantly influence people's comfort in riding an AV. Familiarity and demographic variables do not have a strong or significant direct impact on comfort.

Variable	B	Standard error	Beta	t	Significance
Tech adoption	.2	.034	.188	5.654	<.001
Familiarity	.206	.035	.194	5.867	<.001
Gender	-.26	.064	-.128	-3.98	<.001
Race – Black	-.135	.097	-.043	-1.385	.166
Birth Year	.011	.002	.19	5.971	<.001
Household Income	.003	.1	.01	.281	.78
Level of Education	.004	.01	.014	.443	.66
Constant	-21.732	3.65		-5.953	<.001

Table 23:Regression, Safety index, Adj $R^2 = .199$

In Table 23, we have the results of a regression analysis for the Safety index. The variables included in the regression model are:

1. Tech adoption: The coefficient (B = 0.2) suggests a positive effect of tech adoption on the Safety index. It is statistically significant at a very high level ($p < 0.001$), indicating that higher levels of tech adoption are associated with increased perceptions of safety for AVs.

2. Familiarity: The coefficient (B = 0.206) indicates a positive effect on the Safety index. It is statistically significant at a very high level ($p < 0.001$), suggesting that higher levels of familiarity with AVs are associated with increased perceptions of safety.
3. Gender: The coefficient (B = -0.26) suggests a negative effect on the Safety index for gender. It is statistically significant ($p < 0.001$), indicating that being female is associated with lower perceptions of safety.
4. Race – Black: The coefficient (B = -0.135) indicates a negative effect on the Safety index for being Black. However, it is not statistically significant at the conventional threshold of 0.05 ($p = 0.166$).
5. Birth Year: The coefficient (B = 0.011) suggests a positive effect on the Safety index for birth year. It is statistically significant at a very high level ($p < 0.001$), indicating that younger individuals tend to have higher perceptions of safety.
6. Household Income: The coefficient (B = 0.003) suggests a positive effect on the Safety index for household income. However, it is not statistically significant ($p = 0.78$), indicating that there is no clear relationship between income and perceptions of safety.
7. Level of Education: The coefficient (B = 0.004) indicates a positive effect on the Safety index for level of education. However, it is not statistically significant ($p = 0.66$), suggesting that education level does not significantly influence perceptions of safety.

The adjusted R-squared value of 0.199 suggests that the included variables collectively explain approximately 19.9% of the variance in the Safety index. Overall, the analysis indicates that tech adoption, familiarity, gender, and birth year are significant predictors of the Safety index. Factors such as race, household income, and level of education do not show significant associations with perceptions of safety. Familiarity with AVs is the strongest predictor of feelings of safety.

Variable	B	Standard error	Beta	t	Significance
Gender	-.095	.06	-.047	-1.59	.113
Race – Black	-.855	.093	-.272	-9.23	<.001
Birth Year	.018	.002	.314	10.68	<.001
Household Income	.035	.01	.12	3.76	.001
Level of Education	.011	.01	.035	1.122	.262
Constant	-34.77	3.401		-10.223	<.001

Table 24:Regression, Early/Late adopters of Technology index, Adj $R^2 = .197$

Table 24 presents the results of a regression analysis for the Early/Late adopters of Technology index. Gender has a coefficient (B = -0.095) which suggests a negative effect on the Early/Late adopters of Technology index for gender. However, it is not statistically significant at the conventional threshold of 0.05 (p = 0.113), indicating that gender does not have a significant influence on early or late adoption behavior. Race – Black has a coefficient (B = -0.855) which indicates a negative effect on the Early/Late adopters of Technology index for being Black. It is statistically significant at a very high level (p < 0.001), suggesting that individuals who identify as Black are more likely to be late adopters of technology compared to early adopters. Birth Year has a coefficient (B = 0.018) suggesting a positive effect on the Early/Late adopters of Technology index for birth year. It is statistically significant at a very high level (p < 0.001), representing that younger individuals are more likely to be early adopters of technology. The variable household Income has a coefficient (B = 0.035) indicates a positive effect on the Early/Late adopters of Technology index for household income. It is statistically significant ($p = 0.001$), suggesting that individuals with higher incomes are more likely to be early adopters of technology. Level of Education has a coefficient (B = 0.011) showing a positive effect on the Early/Late adopters of Technology index for level of education. However, it is not statistically significant ($p = 0.262$), indicating that education level does not significantly influence early or late adoption behavior.

The constant term (intercept) is -34.77, indicating the baseline level of the Early/Late adopters of Technology index when all other variables are zero. The adjusted R-squared value of 0.197 suggests that the included variables collectively explain approximately 19.7% of the variance in the Early/Late adopters of Technology index. Overall, the analysis indicates that race, birth year, and household income are significant predictors of the Early/Late adopters of Technology index. Factors such as gender and level of education do not show significant associations with early or late adoption behavior. Age is the best predictor of technology adoption.

Variable	B	Standard error	Beta	t	Significance
Gender	-.627	.056	-.331	-11.18	<.001
Race – Black	-.062	.086	-.021	-.722	.47
Birth Year	.01	.002	.185	6.293	<.001
Household Income	.033	.01	.117	3.693	<.001
Level of Education	.027	.01	.096	3.04	.002
Constant	-17.392	3.196		-5.441	<.001

Table 25:Regression, Familiarity with AV, Adj $R^2 = .18$

Table 25 highlights the results of a regression analysis examining the relationship between Familiarity with AV (Autonomous Vehicles) and several demographic variables. The following findings can be observed:

Gender: The coefficient for gender (B = -0.627) suggests a negative impact on Familiarity with AVs, indicating that gender may influence individuals' level of familiarity with autonomous vehicles. The statistical analysis reveals that this relationship is highly significant ($p < 0.001$), indicating that gender significantly affects familiarity with AV. Specifically, it suggests that females may be less familiar with AV compared to males.

Race – Black: The coefficient for race – Black (B = -0.062) indicates a negative influence on Familiarity with AV for individuals identifying as Black. However, the statistical analysis shows that this relationship is not statistically significant ($p = 0.47$), suggesting that race, specifically being Black, does not have a substantial impact on familiarity with AV.

Birth Year: The coefficient for birth year ($B = 0.01$) demonstrates a positive effect on Familiarity with AVs, indicating that younger individuals tend to be more familiar with autonomous vehicles. This relationship is highly significant ($p < 0.001$), suggesting that age plays a significant role in determining familiarity with AV.

Household Income: The coefficient for household income ($B = 0.033$) reveals a positive association with Familiarity with AV. This suggests that individuals with higher household incomes are more likely to be familiar with autonomous vehicles. The relationship is statistically significant ($p < 0.001$), indicating the importance of income in determining familiarity with AV.

Level of Education: The coefficient for level of education ($B = 0.027$) suggests a positive influence on Familiarity with AVs for higher levels of education. This implies that individuals with higher education levels tend to be more familiar with autonomous vehicles. The relationship is statistically significant ($p = 0.002$), indicating that education level plays a role in determining familiarity with AV. Overall, the regression analysis indicates that gender, birth year, household income, and level of education significantly influence familiarity with AV. However, the variable race, specifically being Black, does not appear to have a significant impact on familiarity with autonomous vehicles. Age is the strongest predictor of familiarity.

Figure 5 presents the path analysis diagram representing the relationships between variables in a statistical model. It illustrates the paths or direct and indirect effects between variables, as well as the corresponding beta values that quantify the strength and direction of these relationships. The beta values represent the amount of change in the dependent variable associated with a one-unit change in the independent variable in standardized units of measurement. A positive beta value indicates a positive relationship, where an increase in the independent variable is associated with an increase in the dependent variable. Conversely, a negative beta value indicates a negative relationship, where an increase in the independent variable is associated with a decrease in the dependent variable. The diagram below with beta values indicates that:

- The demographic variables have no direct effect on willingness to ride and time to ride, but have an indirect effect through tech adoption index, familiarity with AVs index, and overall safety index.
- Gender has a negative effect on perceptions of overall safety and the time to ride index.
- Familiarity with AVs as well as Tech adoption variables have no direct effect on willingness to ride and time to ride but have an indirect effect through perceptions of overall safety.
- Overall safety strongly influences willingness to ride in an AV and time to ride in AV variables.

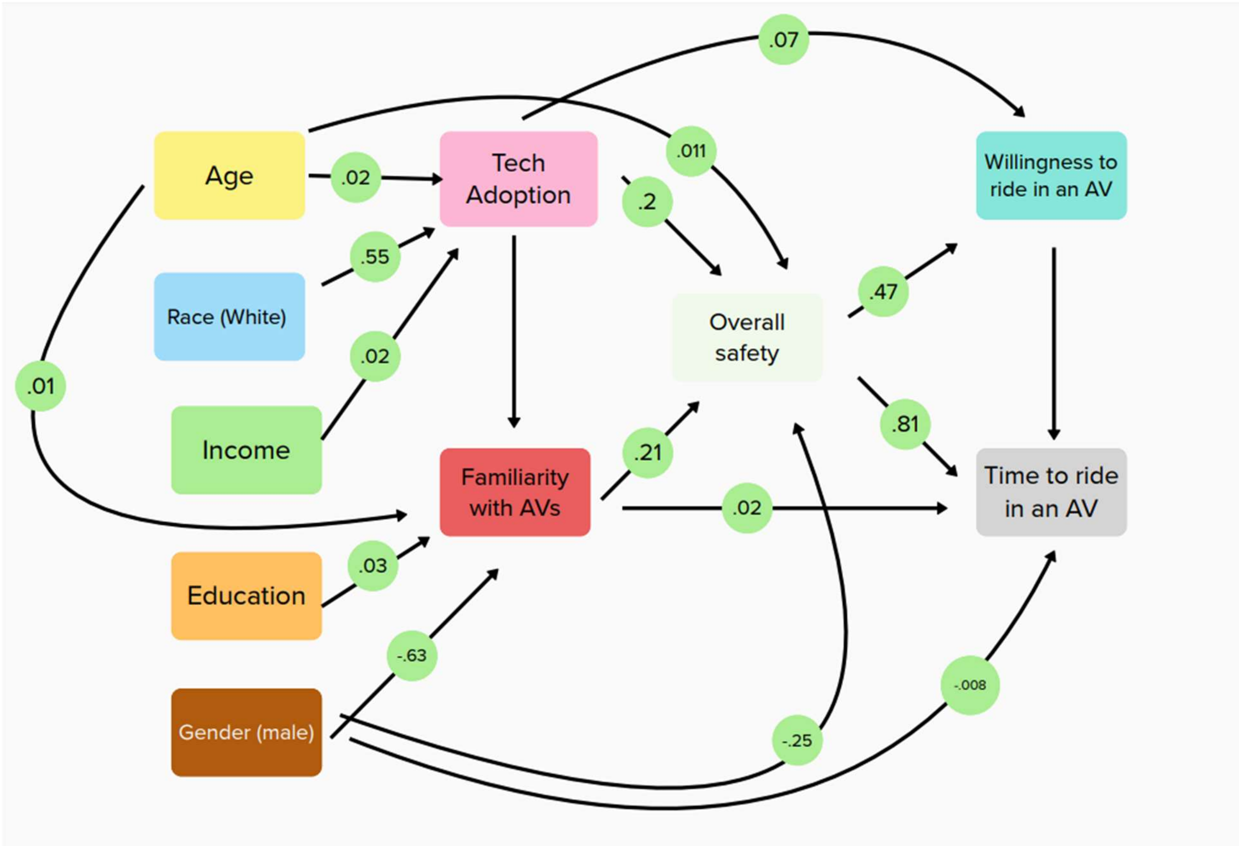

Figure 5:Path Analysis (Beta values)

Summary

The study examines attitudes towards autonomous vehicles (AV) by analyzing frequency data regarding respondents' familiarity with AV technology. Approximately 29% of the participants are moderately familiar with AV technology (n = 290), while 32% are unfamiliar. Only 15% expressed their willingness to ride in an AV, whereas 41% were unwilling, and an additional 28% remained uncertain. It is evident that individuals predominantly perceive riding in an AV as very safe or somewhat safe under specific conditions, such as light traffic (47%, n = 461), daytime (48%, n = 469), and within their own town (45%, n = 448). Conversely, most people would feel unsafe riding in an AV during heavy traffic (77%, n = 754), at night (73%, n = 728), and on the highway (72%, n = 715). Overall, however, respondents still indicate that they are unsure or unwilling to ride in an AV.

Results indicate that individuals would feel more comfortable riding in an AV in 5-10 years (43%) or after a period of 10 years (47%) compared to within the next 0-4 years. Overall, respondents exhibited varying levels of concern, with a significant number expressing they were either somewhat or very concerned regarding potential dangers associated with AVs, such as software hacking (80%), accidents (87%), and vehicle breakdowns (79%). These fears and general lack of familiarity may well account for why respondents would only consider riding in an AV over the longer term.

To assess whether residents of Michigan have altered their attitudes towards autonomous vehicles (AVs) over time, a comparison was conducted between responses from the 2017 State of the State Survey (SOSS), which also included AV-related questions. The rationale behind this analysis was to determine if increased familiarity with AV technology has influenced people's willingness to engage with it. The comparison revealed 79% of respondents expressed fear towards self-driving cars in 2022. This represents a significant increase of 50% compared to 2017 when only 26% harbored such fears. The survey indicated that as people become more acquainted with AV technology, their concerns regarding its potential dangers intensified. It is possible that as people become more familiar with AV technology, they develop a nuanced view that includes both increased comfort and heightened concerns. This finding might indicate that the participants' level of awareness and critical thinking is evolving as they gain more knowledge about AVs. Another notable finding from the survey was that 22% of respondents now feel completely comfortable riding in an autonomous vehicle, signifying a noteworthy 21% increase from 2017. This suggests a divergence among respondents, with some individuals growing more comfortable over time while others becoming increasingly apprehensive about AVs.

The objective of constructing the regression equation was to determine the significant correlations between the exogenous demographic variables, which act as driving factors in the model used in this study, and attitudes towards autonomous vehicles (AVs). The demographic group most inclined to ride in autonomous vehicles (AV) consists primarily of young, single, and white males, whereas Black males exhibit the highest level of unwillingness. Those respondents who are more familiar with AV technology tend to be educated males with higher household incomes. Individuals identifying as Hawaiian Pacific Islander, Asian, Black, American Indian, Alaskan Native, and Hispanic are less likely to feel comfortable riding in AVs. Furthermore, the results indicate that individuals who are early adopters of other technologies are more likely to experience a sense of ease when it comes to riding in AVs.

In summary, the analysis underscores the significant impact of factors like technology adoption and perceived safety on people's comfort levels with autonomous vehicles (AVs). Conversely, safety concerns, familiarity, and other demographic variables have relatively less influence in shaping comfort levels. It is worth noting that age is the only demographic variable that exhibits a significant direct correlation with comfort, indicating that younger respondents are more likely to feel at ease when riding in an AV across all time periods. Furthermore, perceptions of safety emerge as the most reliable predictor of comfort levels.

CHAPTER 5 - Discussion & Conclusion

This study was designed to delve into the collective opinions and concerns of the general public regarding the safety of autonomous vehicles in Michigan. It seeks to examine the various factors that shape public perceptions of AV safety, including demographics, previous technology adoption, and familiarity with AV technology. Additionally, the research aims to pinpoint early adopters of autonomous vehicles in Michigan and scrutinize the distinguishing characteristics and motivations that set them apart from individuals who have not embraced this technology. Previous research has found that the socio-demographic factors linked to higher perceptions of autonomous vehicle (AV) safety are also tied to a greater inclination to adopt AV technology (Smith & Caiazza, 2017; Payre, Cestac & Delhomme, 2014; Hulse, Xie & Galea, 2018). Additionally, studies have indicated that perceptions of safety are connected to interest in and intended usage of AVs, underscoring the significance of understanding safety perceptions in predicting the potential future adoption of this technology.

Autonomous vehicles (AVs) hold great promise in addressing current transportation challenges and delivering a range of benefits, such as reducing accidents, improving traffic flow, enhancing mobility, and increasing fuel efficiency. They are anticipated to make travel safer, more affordable, comfortable, and sustainable, thereby providing greater accessibility to children, seniors, and individuals with disabilities. Despite the potential for improved safety and quality of life, many individuals exhibit hesitancy towards adopting AV technology due to concerns about safety, liability, and control. The perception of AV safety plays a pivotal role in their implementation, development, and eventual usage. Research demonstrates the substantial safety potential of AVs and highlights the importance of understanding public perceptions in evaluating their future adoption, governing policies, and infrastructure investments. However, limited attention has been given to user perspectives, such as determining the time and conditions under which AVs are considered safe to use, as well as identifying the factors that contribute to early adoption of this complex innovation. Similarly, little effort has been made to assess whether early adopters of other technologies will also be early adopters of AVs or if their adoption timeline will differ.

Autonomous vehicles (AVs) are expected to bring forth numerous benefits, including accident reduction, improved traffic flow, enhanced mobility, and increased fuel efficiency (NHTSA, 2017). However, when people were surveyed about AVs, safety emerged as the most prevalent concern (Casley, Jardim, & Quartulli, 2013). The perceived safety of AVs significantly influences their implementation, development, and overall usage. Extensive research highlights the considerable safety potential of AVs and emphasizes the importance of understanding public perceptions in evaluating the future adoption of this technology. Notably, AVs are anticipated to make travel safer, more affordable, comfortable, and sustainable, thus extending the accessibility of car travel to children, seniors, and individuals with disabilities (Fagnant and Kockelman, 2015). For significant portions of the population, traditional driving options are not feasible due to factors such as the cost of car ownership, learning to drive, licensing difficulties, or health, disability, and age-related constraints.

AV technology has the potential to address the challenges that lead to socio-economic disadvantages for these communities and provides equitable transportation options and personalized choices, thereby empowering those who are unable to drive and promoting fairness and inclusivity across socio-demographic groups. To realize these societal and individual benefits, widespread and swift adoption of AV technology is necessary. Consequently, there is a clear demand for supportive state and local government policies that facilitate the deployment of these technologies.

Demographic factors and Concerns

The quantitative analysis in this study showed that the demographic group most inclined to ride in autonomous vehicles (AV) consists primarily of young, single, and white males, and those respondents who are more familiar with AV technology tend to be educated with higher household incomes. The results from this study support the findings of similar research endeavors on public perceptions of positivity towards AVs by Hulse, Xie, and Galea (2018) as well as research on increased perceptions of safety (Smith & Caiazza, 2017; Schoettle & Sivak, 2014; Nielsen & Haustein, 2018).

Moreover, it is interesting to note that comparing the existing SOSS with 2017 data, 79% of individuals expressed fear towards self-driving cars, marking a significant increase of about 50% compared to the 26% fear rate recorded in 2017. The survey findings suggest that as people become more familiar with autonomous vehicle (AV) technology, their concerns about potential dangers may escalate. Another notable statistic from the survey reveals that 22% of respondents now feel completely comfortable riding in an autonomous vehicle, indicating a substantial 21% rise from 2017. This indicates a potential divergence among respondents, with some becoming increasingly at ease with AVs over time while others become more apprehensive. The increased familiarity with autonomous vehicles from 2017 to 2022, coupled with heightened concerns about their dangers, can be attributed to several factors. Autonomous vehicles have received significant media attention during this period. While media coverage has helped familiarize people with the concept of autonomous vehicles and their potential benefits, it has also highlighted incidents and accidents involving autonomous vehicles. Negative incidents tend to receive more attention, leading to increased concerns about the safety of autonomous vehicles. Additionally, the few highly publicized accidents involving autonomous vehicles during this timeframe such as the Uber self-driving car accident in 2018 or the Tesla Autopilot crashes, can have a lasting impact on public perceptions. Such accidents can reinforce concerns about the reliability and safety of autonomous vehicles, even though statistically they might be safer than human-driven vehicles overall. Moreover, despite increased familiarity, there may still be limited understanding among the public about the technology behind autonomous vehicles. People may not fully grasp the capabilities and limitations of autonomous systems, leading to apprehension and concerns about their safety. Misconceptions or misinformation about technology can amplify these concerns. It is also worth mentioning that the period from 2017 to 2022 represents a transition phase in autonomous vehicle development. During this time, autonomous technologies were advancing, but widespread deployment and standardization were still in progress. The uncertainties and challenges associated with this transitional phase can contribute to concerns about safety as people consider the potential risks and uncertainties involved in the technology's adoption.

Familiarity and comfort level with AV technology

According to the results of this study, there is a statistically significant linear relationship between familiarity with AV technology and a higher comfort level when riding in an AV, regardless of the time frame. This implies that increased familiarity with AV technology is associated with an elevated comfort level when riding in an AV at any given time. This relationship holds true regardless of the specific time frame being considered. In simpler terms, the more familiar individuals are with AV technology, the more comfortable they feel when riding in an AV, regardless of when the ride takes place. This implies that becoming more acquainted with AV technology has a positive impact on the comfort experienced during AV rides. The study suggests that as people gain more knowledge and familiarity with AV technology, their level of comfort while riding in AVs tends to rise. Whether it is immediate or long-term familiarity, the connection between familiarity and comfort remains consistent.

The correlation between familiarity with AV technology and how concerned respondents are with the dangers of AVs such as hacking of AV software is not statistically significant. Individuals who have a higher level of familiarity with autonomous vehicles (AVs) exhibit significantly less concern regarding software or hardware malfunctions and potential vehicle breakdowns. In other words, the level of familiarity with AV technology does not have a significant impact on how concerned respondents are about potential software or hardware malfunctions, as well as the possibility of vehicle breakdowns.

Furthermore, the study reveals that individuals who possess a higher level of familiarity with AVs tend to exhibit significantly less concern regarding these potential dangers. This suggests that those who are more familiar with AV technology may have a greater understanding or trust in the safety and security measures implemented in AV systems, leading to reduced levels of concern about software or hardware malfunctions and vehicle breakdowns.

The study identified several significant factors that predict a person's comfort level with autonomous vehicles (AVs). These factors include younger age, higher education level, a positive attitude towards AV technology, and a tendency to adopt technology early. This implies that individuals who are younger, more educated, have a positive view of AV technology, and are early adopters of technology are more likely to feel comfortable when riding in AVs. Additionally, the results indicate that there is a notable correlation between gender and the level of comfort in riding an AV under specific conditions. Specifically, this correlation is observed in situations such as light traffic, daytime travel, and within one's own town where women appear to be more comfortable under these conditions. This finding supports the initial research question, which suggests that public perception of AV safety is influenced by different timeframes and conditions.

The factor analysis results suggest that there are four conceptually different aspects regarding attitudes toward AVs: Comfort with AV index, Early adoption index, Concern index, and Safety index. The demographic profile of individuals most inclined to ride in an AV consists of younger, single, and white males. Conversely, Black males tend to be the least willing to ride in an AV. Additionally, the study findings indicate that respondents who exhibit a higher level of familiarity with AV technology tend to be educated males with higher household incomes. Moreover, the results demonstrate that individuals who feel comfortable riding in an AV are typically young, single, white males with higher household incomes. Conversely, individuals identifying as Hawaiian Pacific Islander, Asian, Black, American Indian, Alaskan native, and Hispanic are less likely to feel at ease riding in an AV. The study reveals that individuals who are early adopters of other technologies are more likely to exhibit comfort with AVs.

These findings support the studies conducted by Smith and Caiazza (2017), Payre, Cestac, and Delhomme (2014), and Hulse, Xie, and Galea (2018) that identified a correlation between socio-demographic factors and both increased perceptions of AV safety and a higher intention to adopt AV technology. Additionally, the only demographic variable that is significantly correlated with comfort is age meaning younger respondents are more likely to be comfortable riding in an AV in all time periods. These findings go against the findings of Zumud et al. (2016) and Shin and Shunsuke (2017) who found no correlation between interest in or intention to use automated vehicles and age. Perceptions of safety are the best predictor of comfort levels. These results answer the second and third research questions about factors influencing the willingness to use autonomous vehicles in the future and the public's perceptions regarding the various types of fears associated with riding in AVs.

Attitudes toward AVs

The multiple regression model in this study identifies connections between early technology adoption and attitudes toward AVs. There is a positive correlation between early adoption of a variety of technologies and willingness to ride in an AV, comfort in using AVs, familiarity with AVs, perceptions of AV safety, and concerns about AVs. The significance levels associated with these correlations reflect the level of confidence in the observed relationships. However, it should be noted that the concern index, which represents worries about potential AV malfunctions, may not exhibit as strong of a relationship as other indexes, such as willingness to ride and the specific timeframes in which respondents are willing to ride in an AV.

Further, the regression analysis reveals that safety is the most influential factor in predicting the willingness to ride in an AV, whereas other variables including technology adoption, concerns, familiarity, and demographic factors have either weak or non-significant effects. These results answer the fourth research question about individuals who embrace new technologies early on showing a greater tendency to be early adopters of autonomous vehicle technology.

Path Analysis

Path analysis is a technique used for assessing causal models by investigating the connections between the dependent variable and independent variables. It allows for the estimation of both the size and significance of these causal links. Initially, a diagram is created to visually represent the relationships between the variables. In path analysis, it is essential to arrange the variables in a logical and time-ordered sequence from left to right. Operationally, path analysis involves a series of multiple regression equations that run from right to left. The beta statistic, obtained from the successive multiple regressions, is depicted on each path. However, it is important to note that the data used in path analysis are cross-sectional, and therefore the causal implications are based on logical reasoning, with the paths indicating the strength of the relationships (Everitt and Dunn, 1991). The analysis proceeded with five regressions, each focusing on specific relationships within the model. The results indicated that the included variables collectively explain approximately 44.5% of the variance in the willingness to ride in an AV. The analysis revealed that factors such as tech adoption and perceived safety significantly impact people's willingness to ride in an AV. Familiarity and demographic variables, on the other hand, do not have a strong or significant direct influence on the willingness to ride although they have indirect effects through technology adoption and familiarity.

Early Adopters

Literature suggested that identifying and targeting early adopters of an innovation could yield significant benefits (Goldsmith & Flynn, 1992; Mcdonald & Alpert, 2007). However, there is a scarcity of research focused on discerning the unique characteristics that distinguish early adopters from late adopters (Rijnsoever & Donders, 2009) specifically within the realm of autonomous vehicle technology. The presence of early adopters is crucial for the success of technological advancement as they provide valuable insights to companies and policymakers regarding the practical implementation of the new technology. Moreover, early adopters can play a pivotal role in instilling confidence in others by demonstrating the safety and efficacy of the technology. This study aimed to investigate whether individuals who have embraced early adoption of various technologies, such as smartphones, text messaging, social media, transportation apps, car-sharing services like Uber/Lyft, and smart home technology, are more inclined to be early adopters of autonomous vehicles. The Pearson correlation coefficients were calculated to examine the relationship between the comfort level for riding in autonomous vehicles (AVs) at different time frames and the early adoption of various technologies. These correlation coefficients provide information about the strength and direction of the association between these variables. The correlations indicate that individuals who exhibit early adoption behavior across various technologies, including social media, transportation apps, car-sharing, smart home technology, smartphones, and text messaging, tend to demonstrate higher comfort levels when it comes to riding autonomous vehicles (AVs) across different time periods. These findings also answer the fourth research question about individuals who embrace new technologies early on show a greater tendency to be early adopters of autonomous vehicle technology.

The findings of the study suggest that positive public perceptions and expectations regarding the safety of autonomous vehicles (AVs) can play a crucial role in encouraging early adoption, particularly among young males who are more inclined to take risks. These individuals may be more likely to embrace AV technology if they perceive it as safe and reliable.

However, the study also emphasizes the importance of addressing safety concerns related to AV implementation. To have a significant impact on the road, AV technology must surpass the safety standards of human drivers. This implies that AVs need to demonstrate a higher level of safety and reliability compared to traditional human-driven vehicles.

The survey highlights that by effectively addressing safety concerns and ensuring that AVs meet rigorous safety standards, there is potential for AVs to enhance road safety conditions in areas where significant challenges currently exist. It suggests that in states or regions facing substantial road safety issues, AV adoption, particularly among young drivers, could contribute to reducing the global road safety disparity.

Next Steps

This dissertation research raises a number of opportunities and next steps for future research:

1. Comparative Analysis: Conducting a comparative analysis of public perceptions and early adoption patterns in different regions or states outside of Michigan. This can provide insights into regional variations and factors influencing public attitudes toward AV safety.
2. Longitudinal Study: Conducting a longitudinal study to track changes in public perceptions and adoption rates over time. This can help understand the dynamics of perception shifts, adoption trends, and the impact of evolving AV technology on public acceptance.
3. Qualitative Research: Conducting qualitative research, such as interviews or focus groups, to gain in-depth insights into the motivations, concerns, and experiences of early adopters and non-adopters. This can provide a richer understanding of the factors influencing adoption decisions.
4. Risk Perception Analysis: Investigating the factors influencing risk perception related to autonomous vehicles. Explore how demographic variables, prior technology adoption experiences, and familiarity with AV technology influence individuals' risk perception and subsequent adoption decisions.
5. Policy and Regulatory Analysis: Analyzing the existing policies and regulations related to autonomous vehicles in Michigan and other states and exploring their impact on public

perceptions and adoption rates. Examining how policy changes and regulations can address concerns and facilitate wider acceptance of AV technology.

6. Impact on Transportation Infrastructure: Studying the potential impact of increased AV adoption on transportation infrastructure, including road design, traffic management, and public transportation systems. Analyzing how infrastructure planning and investments can support the safe and efficient integration of AVs.
7. User Experience and Human-Machine Interaction: Investigating the user experience and human-machine interaction aspects of autonomous vehicles. Examining user preferences, usability, trust in AV technology, and challenges faced during AV operation to enhance user acceptance and design more user-friendly AV systems.
8. Economic and Social Impacts: Assessing the economic and social impacts of widespread AV adoption, such as changes in employment patterns, mobility patterns, urban planning, and environmental sustainability as well as studying the potential benefits and challenges associated with large-scale AV deployment.

Limitations

This study does have several limitations. One limitation of this study is that it relied on a cross-sectional survey design. Cross-sectional surveys capture data at a specific point in time, providing a snapshot of the population's characteristics and attitudes. However, this design does not allow for the examination of causal relationships or changes over time. It provides information about associations at a particular moment, but it cannot establish the directionality of the relationships or determine if one variable precedes another.

Additionally, there is uncertainty regarding the time ordering of variables in the study. As a cross-sectional survey, it is difficult to determine if familiarity with AV technology influenced the comfort level when riding in an AV or if it was the other way around. It is possible that individuals who were more comfortable with AVs sought out opportunities to become familiar with the technology. Therefore, the causal direction between familiarity and comfort cannot be established with certainty.

These limitations highlight the need for future research to employ longitudinal designs that capture data over time. Longitudinal studies can provide a clearer understanding of the temporal relationships between variables and offer insights into the potential causal effects. By tracking changes in familiarity with AV technology and comfort levels over time, researchers can establish more robust conclusions regarding the associations between these variables and other variables under study.

Another limitation of this study is that the sample used in the research may not fully represent the entire US population. The findings of the study were based on a specific sample of participants in Michigan, which may have resulted in a biased representation of the population. Sampling bias could have occurred as the participants were selected from a particular region, demographic group, or had specific characteristics that are not representative of the broader population. This limitation reduces the generalizability of the study's findings and limits the ability to make accurate inferences about the entire US population's perceptions or behaviors regarding the topic of study.

Policy implications

The findings of this research have a number of implications for policy related to AVs which are summarized below.

- Promoting Education and Awareness: Governments should prioritize public education and awareness campaigns to address misconceptions and enhance understanding of autonomous vehicle safety. These campaigns should provide accurate information about the technology, its safety features, and ongoing research and development efforts. By improving public knowledge, policymakers can shape positive perceptions and alleviate concerns about AV safety.

- Safety Standards and Regulation: Policymakers need to establish clear and comprehensive safety standards and regulations for AVs. These standards should encompass not only vehicle performance but also cybersecurity, data privacy, and ethical considerations. By setting robust safety requirements and regulations, policymakers can build trust among the public and ensure that AV technology is held to a high standard of safety.
- Collaboration with Industry: Close collaboration between policymakers and industry stakeholders is essential to address public concerns regarding AV safety. Governments should actively engage with manufacturers, technology companies, and researchers to understand the latest advancements, evaluate safety protocols, and ensure transparency in the development and deployment of AV technology. This collaboration can help policymakers make informed decisions regarding safety regulations and foster a sense of collective responsibility in addressing safety concerns.
- Testing and Certification: Governments should establish rigorous testing and certification processes for AVs. This includes conducting comprehensive evaluations of AV safety features, performance in various scenarios, and cybersecurity resilience. Independent third-party testing organizations can play a vital role in verifying the safety and reliability of AV technology. Transparent certification processes will instill confidence in the public and encourage the adoption of AVs.

- Addressing Liability and Insurance: Policymakers need to address liability and insurance issues associated with AVs. Clear frameworks should be developed to determine responsibility in case of accidents or malfunctions involving AVs. Additionally, insurance policies should be adapted to accommodate the unique risks and safety considerations associated with autonomous driving. This will provide clarity for both AV manufacturers and consumers and contribute to building public trust in AV safety.
- Long-Term Safety Monitoring: Continuous monitoring and evaluation of AV safety should be established as an ongoing process. Governments and regulatory bodies should invest in research, data collection, and analysis to identify potential safety concerns and address them proactively. This monitoring will help in refining safety standards, updating regulations, and ensuring that AV technology continues to meet or exceed the safety levels of human-driven vehicles.
- International Collaboration: Given the global nature of AV technology, policymakers should promote international collaboration and harmonization of safety standards and regulations. Sharing best practices, research findings, and safety data across borders will facilitate the development of consistent global safety frameworks and enhance public trust in AVs. Governments can also work with companies to establish safety standards, protocols for testing and validation, and guidelines for responsible deployment.
- Transparency and Communication: Governments should prioritize transparent communication to address public concerns and provide accurate information about the safety measures and risk mitigation strategies employed in autonomous vehicles (AVs). This includes sharing details about the technology, its limitations, and ongoing safety

assessments. Clear and accessible channels of communication can help alleviate public fears and build trust in AVs.

- Safety Assurance in Challenging Conditions: Addressing the concerns and discomfort associated with heavy traffic, nighttime, and highway driving, it is crucial to develop and demonstrate the safety capabilities of AVs in these challenging conditions. Further research and development efforts should focus on improving the AV technology's performance and reliability in these scenarios to instill confidence and alleviate apprehensions among the public.
- Education and Awareness Campaigns: Conducting targeted education and awareness campaigns to inform the public about the safety features and advantages of AVs, particularly highlighting their effectiveness in light traffic and daytime driving. By increasing public knowledge and understanding, misconceptions can be dispelled, and individuals may develop a more positive perception of AV safety.
- Infrastructure Planning and Design: Considering the specific concerns raised by the public regarding nighttime and highway driving. Enhancing road infrastructure and lighting conditions in these contexts can contribute to increased confidence and perceived safety in AVs. This may involve implementing better lighting systems, clear signage, and road design considerations that accommodate AV technology.
- Gradual Introduction and Testing: Begin implementing AVs in areas with lighter traffic and during daytime hours, where public perception of safety is more favorable. This gradual introduction allows for testing, evaluation, and fine-tuning of AV performance and safety measures, further building public trust and confidence.

- Risk Management and Contingency Planning: Policymakers should work with AV manufacturers and relevant stakeholders to develop comprehensive risk management and contingency plans. This includes addressing potential hazards, such as cybersecurity breaches, system failures, or unexpected road conditions. By implementing proactive risk management strategies, policymakers can demonstrate their commitment to public safety and alleviate concerns about the dangers associated with AV technology.
- Robust Cybersecurity Measures: Policymakers must prioritize cybersecurity in AVs to address public concerns regarding the potential dangers of hacking or unauthorized access to vehicle systems. Governments should establish stringent cybersecurity standards, require regular audits, and encourage the adoption of best practices to safeguard AVs against cyber threats. Strengthening cybersecurity measures will help build public confidence in the safety of AVs.
- Public Engagement and Feedback: Policymakers should actively seek public input and feedback regarding AV safety concerns and dangers. This can be done through public consultations, surveys, or dedicated platforms for public engagement. Incorporating public perspectives helps policymakers understand and address specific concerns, fostering public trust and increasing the acceptability of AV technology.
- Incentives for Early Adopters: Governments can consider providing incentives, such as tax credits or subsidies, to early adopters of AV technology. These incentives can help reduce the financial barrier and motivate individuals to embrace AVs sooner. By rewarding early adoption, policymakers can accelerate the adoption rate and create a positive perception of AVs as innovative and desirable transportation options.

- Infrastructure Development: Policymakers need to invest in infrastructure development that supports the deployment of AVs. This includes the installation of dedicated AV lanes, smart traffic management systems, and robust connectivity infrastructure. By creating an environment conducive to AV operations, policymakers can demonstrate their commitment to embracing the technology and enhancing public perception of AVs as safe and efficient modes of transportation.
- Regulatory Frameworks: Policymakers need to establish flexible and adaptive regulatory frameworks to accommodate the rapid evolution of AV technology. Regulations should strike a balance between safety, innovation, and public acceptance. Proactive engagement with industry stakeholders and experts can help policymakers develop effective regulations that address public concerns while allowing for experimentation and progress.

By implementing these policy measures, governments can foster a supportive environment for AV adoption and maximize the potential benefits of autonomous vehicle technology.

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